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Publication date:
2014

Document Version
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Technical University of Denmark

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PhD Thesis
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Printed by:	Vester Kopi August 2014
Cover:	Torben Dolin

Preface

The work presented in this PhD thesis was conducted at the Department of Environmental Engineering of the Technical University of Denmark (DTU) under the supervision of Professor Karsten Arnbjerg-Nielsen, with Professor Henrik Madsen (DHI), and Professor Emeritus Dan Rosbjerg (DTU Environment) as co-supervisors. The work was conducted from April 2011 to June 2014.

The PhD project was funded by the Danish Council for Strategic Research as part of the RiskChange project (contract no. 10-093894). Part of the work was carried out with the support of FloodFreq COST Action ES0901 and The Foundation for Development of Technology in the Danish Water Sector as part of the project Precipitation in a Future Climate (contract no. 7492-2012).

The content of the thesis is based on five scientific journal papers:

- **I** **Sunyer, M.A.**, Madsen, H., Rosbjerg, D., and Arnbjerg-Nielsen, K.: Regional interdependency of precipitation indices across Denmark in two ensembles of high-resolution RCMs, Journal of Climate, 20, 7912–7928, doi: 10.1175/JCLI-D-12-00707.1, 2013.
- **II** **Sunyer, M.A.**, Sørup, H.J.D., Christensen, O.B., Madsen, H., Rosbjerg, D., Mikkelsen, P.S., and Arnbjerg-Nielsen, K.: On the importance of observational data properties when assessing regional climate model performance of extreme precipitation, Hydrology and Earth System Sciences, 17, 4323–4337, doi: 10.5194/hess-17-4323-2013, 2013.
- **III** **Sunyer, M.A.**, Madsen, H., Rosbjerg, D., and Arnbjerg-Nielsen, K.: A Bayesian approach for uncertainty quantification of extreme precipitation projections including climate model interdependency and non-stationary bias, Journal of Climate, accepted.
- **IV** **Sunyer, M.A.**, Hundecha, Y., Lawrence, D., Madsen, H., Willems, P., Martinkova, M., Vormoor, K., Bürger, G., Kriaučiūnienė, J., Loukas, A., Osuch, M., Vasiliades, L., and Yücel, I.: Inter-comparison of statistical downscaling methods for projection of extreme precipitation in Europe, Hydrology and Earth System Sciences Discussion, 11, 6167–6214, doi: 10.5194/hessd-11-6167-2014, 2014.
- **V** **Sunyer, M.A.**, Gregersen, I.B., Madsen, H., Luchner, J., Rosbjerg, D., and Arnbjerg-Nielsen, K.: Comparison of different statistical

downscaling methods to estimate changes in hourly extreme precipitation using RCM projections from ENSEMBLES, International Journal of Climatology, in review.

The papers are referred to by their roman numerals throughout the thesis (e.g. Paper **I**).

The following articles, not included in this thesis, were also prepared during the PhD study:

- Mayer, S., Maule, C.F., Sobolowski, S., Christensen, O.B., Sørup, H.J.D., **Sunyer, M.A.**, Arnbjerg-Nielsen, K., and Barstad, I.: Identifying added value in high-resolution climate simulations over Scandinavia, Tellus A. Scope, submitted.
- Hundecha, Y., **Sunyer, M.A.**, Lawrence, D., Madsen, H., Willems, P., Bürger, G., Kriaučiūnienė, J., Loukas, A., Martinkova, M., Osuch, M., von Christierson, B., Vormoor, K., and Yücel, I.: Effect of downscaling climate data on changes in indices of extreme river flow under climate change: A comparative study across Europe, in preparation.
- **Sunyer, M.A.**, Madsen, H., Rosbjerg, D., and Arnbjerg-Nielsen, K.: Effects of climate model interdependency on the uncertainty quantification of extreme rainfall projections, 9th International Workshop on Precipitation in Urban Areas, St. Moritz, Switzerland, 6–9 December 2012.
- **Sunyer M.A.**, Gregersen, I.B., Madsen, H., Rosbjerg, D., and Arnbjerg-Nielsen, K.: Extreme precipitation in a future climate – assessing climate factors at sub-daily scales with regional climate model statistics, 13th International Conference on Urban Drainage, Sarawak, Malaysia, 7–12 September 2014.

June 2014
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In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from DTU Environment, Technical University of Denmark, Miljøvej, Building 113, 2800 Kgs. Lyngby, Denmark, reception@env.dtu.dk.

Acknowledgements

I would like to start by thanking my supervisor Karsten Arnbjerg-Nielsen for guiding and encouraging me during the PhD. Big thanks also go to my co-supervisors Henrik Madsen and Dan Rosbjerg. Thank you all for the many different ways in which you have helped me throughout these three years.

Many thanks go to Christian Onof for the motivating discussions and for all the help during my external stays at Imperial College London.

I am grateful to RiskChange for funding my research. I am also thankful for having had the opportunity of being part of FloodFreq and the project Precipitation in a Future Climate. Furthermore, the Urban Water Technology Research School, in which I have been enrolled, is acknowledged.

Thanks to my office mates: QianQian, Ida, Helena, Nina, and (almost office mate) Hjalte, who have made of our office a nice cosy place with a nice (and helpful) coffee machine. Warm thanks go to Claire, Silvio, Ana, Julie, Claus, Pernille, Luca, and Sara for filling the days at work with nice moments and laughs. Thanks to all the members of the cake club and all the great colleagues at DTU Environment.

Thank you to all the poppel people: Bertrand, Thanos, Elisa, Guillermo, and Stefania and to all my friends in Copenhagen for all the support, long dinners, and the good times.

A huge amount of support has always arrived from the distance. Thanks George for making this possible and for always being (t)here. A final million thanks go to my parents and family for their patience, encouragement, and love. *Gràcies per tot!*

"Doubt is not a pleasant condition, but certainty is absurd"
-Voltaire

Summary

The latest report from the Intergovernmental Panel on Climate Change (IPCC) states that it is unequivocal that climate change is occurring. One of the largest impacts of climate change is anticipated to be an increase in the severity of extreme events, such as extreme precipitation. Floods caused by extreme precipitation pose a threat to human life and cause high economic losses for society. Thus, strategies to adapt to changes in extreme precipitation are currently being developed and established worldwide. Information on the expected changes in extreme precipitation is required for the development of adaptation strategies, but these changes are subject to uncertainties.

The focus of this PhD thesis is the quantification of uncertainties in changes in extreme precipitation. It addresses two of the main sources of uncertainty in climate change impact studies: regional climate models (RCMs) and statistical downscaling methods (SDMs). RCMs provide information on climate change at the regional scale. SDMs are used to bias-correct and downscale the outputs of the RCMs to the local scale of interest in adaptation strategies.

In the first part of the study, a multi-model ensemble of RCMs from the European ENSEMBLES project was used to quantify the uncertainty in RCM projections over Denmark. Three aspects of the RCMs relevant for the uncertainty quantification were first identified and investigated. These are: the interdependency of the RCMs; the performance in current climate; and the change in the performance of the RCMs from current to future climate.

The interdependency of the RCMs was estimated using two different methods. These led to slightly different results but to the same conclusion; that the RCMs cannot be considered independent.

The performance of the RCMs under current climate conditions was assessed using a range of precipitation indices, metrics, and observational data sets. It was found that these factors have a large influence on the performance estimated for the RCMs. This highlights the fact that it is not possible to identify a single best or worst RCM.

The possible change in the performance of the RCMs under future climate conditions was explored using the relation between the bias of the RCMs and the observed precipitation intensity. For all the RCMs, the magnitude of the

bias depends on the precipitation intensity. Hence, changes in bias can be expected to occur with changes in extreme precipitation.

These findings were taken into account in the development of a Bayesian approach, which quantifies the statistical uncertainty in the change in extreme precipitation. In general, extreme precipitation intensity is expected to increase by the end of the century, but this change is associated with large uncertainties, especially in summer. With a probability of 95%, extreme precipitation is estimated to increase in winter, but in summer the values range from a decrease of 40% to an increase of 40%. A set of tests were carried out to assess the influence of accounting for the interdependency and change in bias of the RCMs in the quantification of uncertainty. The results highlight the importance of taking these two aspects into account. If they are not accounted for there is a risk of underestimating the uncertainty and reaching overconfident results.

The second part of the study addressed the uncertainty arising from SDMs for two applications: river flooding in eleven European catchments; and urban flooding in Denmark. A range of SDMs were applied at daily and hourly resolution to the RCMs in the ensemble. The results for Denmark from both applications showed that in general the SDMs agree on an expected increase in extreme precipitation intensity. The uncertainty was explored by analysing the differences in the results of the SDMs and by comparing them with the differences within the RCM outputs. It was found that even though the variability within the SDMs is smaller than within the RCMs, it is not negligible. For example, in the river flooding application it represents approximately 30% of the total variance.

This study contributes to the understanding of the uncertainties in climate change impact studies arising from RCMs and SDMs. The Bayesian approach suggested is a step forward towards a more comprehensive quantification of the uncertainties in a multi-model ensemble of RCMs. This approach could potentially be extended to include the uncertainty arising from other sources, such as SDMs. Further research is suggested in this direction.

The findings of this study point out that there are large uncertainties in changes in extreme precipitation under climate change conditions. These uncertainties should not be seen as a reason for postponing action on climate adaptation. We have enough knowledge to carry on with the development of adaptation strategies, but their robustness must be ensured by including information on the uncertainties in climate change impact studies.

Dansk sammenfatning

FN's klimapanel (ofte forkortet IPCC ud fra den engelske titel: Intergovernmental Panel on Climate Change) har i deres seneste rapport fastslået, at klimaændringer er en realitet. En stigning i antallet af ekstreme vejrfænomener, såsom skybrud, betragtes som en af de alvorligste følger. Oversvømmelser grundet skybrud kan skabe livstruende situationer og har høje økonomiske omkostninger for samfundet. Tilpasningsstrategier rettet mod ændringer i ekstremregnen bliver derfor udviklet og implementeret på verdensplan. Hertil kræves viden om den forventede ændring i ekstremregnen, som dog er underlagt stor usikkerhed.

Nærværende ph.d.-afhandling omhandler kvantificering af usikkerheden i projekterede ændringer i ekstremregn som følge af klimaændringer. Afhandlingen betragter to vigtige kilder til usikkerhed ved studier af oversvømmelsesrisici under fremtidens klima: regionale klimamodeller og statistiske nedskaleringsmetoder. Fra regionale klimamodeller opnås viden om klimaændringernes effekt på regional skala. De statistiske nedskaleringsmetoder benyttes til at korrigere og nedskalere resultaterne fra de regionale klimamodeller til brug for udvikling af lokale tilpasningsstrategier.

I den første del af ph.d.-studiet blev klimasimuleringer fra den europæiske ENSEMBLES database anvendt til at kvantificere usikkerheden forbundet med de regionale klimamodellers projektion af ændringen i ekstremregn over Danmark. Tre relevante aspekter blev identificeret og undersøgt: Klimamodellernes interne afhængighed, deres fejl ved simulering af nutidens klima, samt ændringen af denne i projektioner for fremtidens klima.

Klimamodellernes interne afhængighed blev estimeret med to forskellige statistiske metoder. Resultatet varierer marginalt med valg af metode, og den overordnede konklusion for begge metoder er, at klimamodellerne i ensemblet ikke kan betragtes som uafhængige.

Fejl i simuleringen af nutidens klima blev vurderet ud fra et bredt udvalg af nedbørskarakteristika, måltal for simuleringsevnen og observationsdatasæt. Alle disse faktorer blev påvist at have stor indflydelse på den individuelle vurdering af klimamodellerne. Dette understeger, at det ikke er muligt at udpege 'den bedste' eller 'den dårligste' klimamodel i ensemblet.

Ændringen i simuleringsfejl i projektionerne for fremtidens klima blev undersøgt ud fra relationen mellem klimamodellens fejl ved simulering af nutidens

klima og den observerede nedbørsintensitet. Det blev påvist, at fejlens størrelse afhænger af intensiteten. Dermed må det forventes, at fejlen vil ændres i takt med ændringer i den ekstreme nedbør.

Til bestemmelse af den samlede statistiske usikkerhed i ændringen i ekstremnedbør blev der udviklet en bayesiansk model, der medtager de tre ovenstående aspekter. Af modelresultaterne kan det konkluderes, at den ekstreme nedbør, overordnet set, må forventes at stige hen mod slutning af dette århundrede, men at ændringens størrelse er forbundet med stor usikkerhed, særligt i sommermånederne. Beregningerne viser, at den ekstreme vinternedbør med 95% sandsynlighed vil stige, mens ændringerne i den ekstreme sommernedbør rangerer fra faldende intensiteter til en stigning på 40%. En række undersøgelser er endvidere udført for at vurdere betydningen af klimamodellernes interne afhængighed og deres simuleringsfejl ved skøn af usikkerheden i ændringen i ekstremregn. Resultaterne viser, at begge aspekter er af stor vigtighed. Medtages de ikke, er der stor risiko for at undervurdere usikkerheden og denmed give resultaterne for stor tiltro.

Anden del af ph.d.-studiet behandlede usikkerheden introduceret af de statistiske nedskaleringsmetoder med fokus på to specifikke anvendelsesområder: Oversvømmelse i oplandet for elleve europæiske flodsystemer og urbane oversvømmelser i Danmark. En række nedskaleringsmetoder blev anvendt på ENSEMBLES klimamodelsimuleringerne med en tidslig opløsning på henholdsvis en time og en dag. Resultaterne for Danmark viser en generel stigning i ekstremnedbør for begge anvendelsesområder uafhængigt af den anvendte nedskaleringsmetode. Usikkerheden fra forskellen i nedskaleringsmetode blev estimeret og sammenlignet med usikkerheden fra klimamodellerne. Det kan konkluderes, at selv om variationen mellem nedskaleringsmetoderne er mindre end variationen mellem klimamodellerne, er den stadig ikke uvæsentlig. I studiet af de europæiske flodsystemer udgør denne f.eks. omkring 30% af den totale varians.

Det samlede ph.d.-studie bidrager til en bedre forståelse af usikkerheder fra klimamodeller og nedskaleringsmetoder, når effekten af klimaændringer analyseres. Den præsenterede bayesianske model giver en ny, bedre og mere gennemgribende tilgang til kvantificering af usikkerhed i et ensemble af klimamodeller. Denne tilgang kan, potentielt set, udvides, så også usikkerheden fra nedskaleringsmetoderne inkluderes i modellen. Fremtidig forskning bør undersøge dette potentiale.

Studiet viser med tydelighed, at der er stor usikkerhed i estimering af den forventede ændring i ekstremregnen som følge af klimaændringer. Denne usikkerhed bør dog ikke lede til en udskydelse af klimatilpasningen. Vores viden omkring effekten af klimaændringerne er tilstrækkelig til udvikling og implementering af klimatilpasningstiltag. Den forbedrede forståelse af usikkerhed bør i den forbindelse benyttes til at sikre udvikling af robuste klimatilpasningsstrategier.

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Abbreviations

BC	Bias correction
BCM	Bias correction of mean
BCMV	Bias correction of mean and variance
BCQM	Bias correction quantile mapping
CA	Climate analogue
CF	Change factor
CFM	Change factor of mean
CFMV	Change factor of mean and variance
CFQM	Change factor quantile mapping
CFQP	Change factor quantile perturbation
CGD	Climate Grid Denmark
DC	Delta change
EPI	Extreme precipitation index
GCM	Global climate model
IPCC	Intergovernmental Panel on Climate Change
MOS	Model output statistics
PP	Perfect prognosis
RCM	Regional climate model
RCP	Representative concentration pathway
$RR_{wn}95$	95^{th} percentile of the wet days precipitation amount
$RR_{wn}99$	99^{th} percentile of the wet days precipitation amount
SDII	Simple daily intensity index
SDM	Statistical downscaling method
SRES	Special Report on Emissions Scenarios
WG	Weather generator
WGD	Weather generator and disaggregator
XDS	Expanded downscaling

1 Introduction

1.1 Background and motivation

The last report from the Intergovernmental Panel on Climate Change (IPCC) confirms that climate change is unequivocal (IPCC, 2013). One of its largest impacts is anticipated to be an increase in the severity of extreme events. In Northern Europe, both the intensity and frequency of extreme precipitation is expected to increase (Christensen and Christensen, 2003; IPCC, 2012), which may lead to an increase in the flood hazard.

Flooding is currently one of the most critical natural hazards in Europe (EEA, 2010). In the last decade, several European countries have suffered severe floods, causing loss of life, displacement of people, and large economic losses (EEA, 2010). In Denmark, Copenhagen was recently flooded in two consecutive years (2010 and 2011), which caused large damages to properties and infrastructure. Under future climate conditions, an increase in the flood hazard can have severe socio-economic consequences. Thus, information on changes in extreme precipitation is needed in the development of the climate change adaptation strategies currently being planned in many European countries (EU Commission, 2009).

In recent years, a large number of studies have focused on the estimation of changes in extreme precipitation at the local scale of interest in adaptation strategies (e.g. river catchment or city), e.g. Arnbjerg-Nielsen (2012), Taye et al. (2011), Willems et al. (2012). Several steps are often followed in these studies, the main ones are: the selection of a climate forcing scenario, global climate model (GCM), regional climate model (RCM), and statistical downscaling method (SDM), see e.g. Willems et al. (2012).

GCMs are physically based models, which simulate the response of the atmosphere and oceans to a climate forcing scenario. The spatial resolution of GCMs is too coarse (typically in the order 100-300 km) to adequately represent extreme precipitation (Fowler et al., 2007; Maraun et al., 2010). Thus, dynamical and statistical downscaling techniques are required to obtain extreme precipitation projections at the local scale (Fowler et al., 2007).

In dynamical downscaling, a RCM is set up for a region of interest (e.g. Europe). RCMs are physically based models, which use GCM outputs as boundary conditions and have a higher spatial resolution (typically in the order 10-50 km) than the GCMs. RCMs are often biased and their spatial resolution might still be too coarse for assessing extreme precipitation at the local scale. Further statistical downscaling of RCMs is needed to obtain bias-corrected high-spatial resolution projections. SDMs are based on the idea that it is possible to define a relationship between the large scale of the RCMs (or GCMs) and the local scale. The outputs from SDMs are then used in impact models such as hydrological models to quantify the impact of climate change on, for example, flood hazard in a city or catchment.

It is generally recognized that each of these steps contributes to the uncertainty in climate change impact studies (Goodess et al., 2007; Wilby and Harris, 2006). The identification of uncertainties in climate change and its potential impacts is one of the points in the IPCC mandate from 1988 (IPCC, 2007). Since then, the assessment and communication of uncertainty has been considered crucial by the IPCC (e.g. IPCC, 2007; IPCC, 2012; IPCC, 2013). However, studies have only recently begun to focus on the uncertainty quantification of changes in climate variables at the local scale.

Most studies addressing the uncertainty in climate variables have focused on the uncertainty in climate model projections (either GCMs or RCMs). Some probabilistic procedures have been suggested to quantify this uncertainty (e.g. Greene et al., 2006; Leith and Chandler, 2010; Tebaldi et al., 2005). Nonetheless, there are remaining challenges to be addressed (Knutti et al., 2010). Two main challenges are: the possible interdependency of the climate models, and the lack of consensus on how to evaluate the performance of the climate models. The uncertainty in the statistical downscaling step has rarely been considered in climate change impact studies.

Most studies addressing uncertainties in climate variables have focused on the mean value of the variables; only a few studies address the uncertainty in extreme precipitation. There is a need for a better understanding of the change in extreme precipitation at the local scale to be able to develop climate change adaptation strategies.

Climate change adaptation strategies must be climate-resilient, i.e. they need to be able to cope with a range of plausible future climate changes (Willems et al., 2012). Hence, information on the uncertainties associated to changes in extreme precipitation is required in the development of these strategies. This must include and combine the different sources of uncertainty in climate change impact studies.

1.2 Research objectives

In this context, the overall aim of this PhD study was to investigate and quantify the main uncertainties associated to changes in extreme precipitation at the spatio-temporal resolution needed in hydrological applications. A better understanding of these uncertainties can improve adaptation strategies and ensure climate resilience. The first part of the research focused on the evaluation of RCM projections and the second part on SDMs.

The two main objectives of the research were to:

1. Evaluate the uncertainty in extreme precipitation projections arising from a multi-model ensemble of RCMs driven by several GCMs.
2. Analyse different SDMs for the downscaling of extreme precipitation projections with focus on river and urban hydrology.

This thesis is based on five papers written as part of the PhD study. The first three papers (Paper **I** to **III**) address the first objective, while the last two papers (Paper **IV** and **V**) focus on the second objective.

The thesis is structured as follows. Chapter 2 describes the different uncertainties in climate change impact studies, reviews the relevant literature, and specifies the characteristics of the uncertainties addressed in this study. Chapter 3 presents the data and case studies. Chapter 4 and 5 describe the methods used and discuss the main results of the two objectives of this research. Chapter 6 presents the main conclusions and Chapter 7 lists the suggestions for further research. Chapter 8 includes the list of references. The five papers can be found in Chapter 9. Figure 1.1 illustrates the outline of the thesis in relation to the research objectives and the main steps in climate change impact studies.

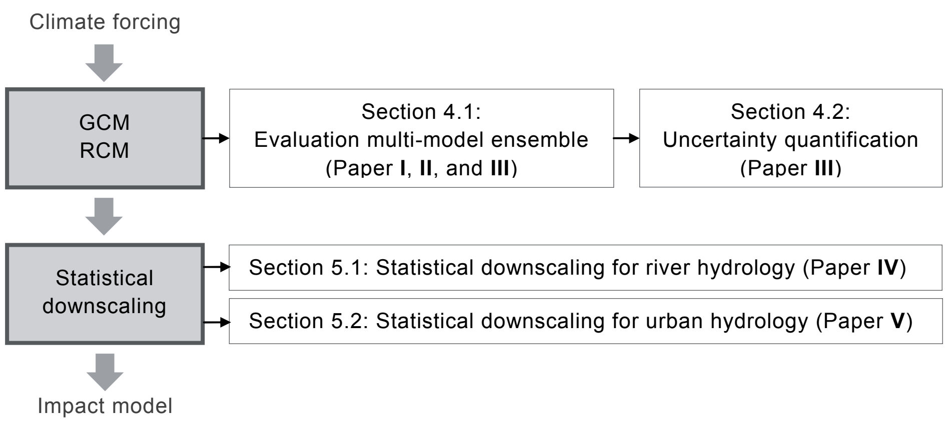

Figure 1.1. Schematic representation of the thesis outline.

2 Uncertainty in climate change impact studies

This chapter describes the uncertainties in climate change impact studies and reviews the relevant literature. It is divided into three parts. The uncertainty cascade is first briefly introduced followed by a more detailed description of the uncertainties in RCMs and SDMs. This chapter also describes the characteristics of the uncertainties from the RCMs and SDMs addressed in this study.

2.1 Uncertainty cascade

The concept of uncertainty is understood and defined in different ways by different communities and disciplines (Beven, 2009; Walker et al., 2003). Here we follow the framework suggested by Refsgaard et al. (2013) to define and characterize the uncertainties in climate change impact studies. We consider that “a person is uncertain if he/she lacks confidence about his/her knowledge relating to a specific question”. This definition was used by Sigel et al. (2010) to establish a framework for perceiving and describing uncertainty in environmental decision-making.

Refsgaard et al. (2013) characterised uncertainties according to three dimensions: level, source, and nature, based on the typology suggested in previous studies (van der Keur et al., 2008; Refsgaard et al., 2007; Walker et al., 2003).

- Level: indicates the classification of uncertainty between deterministic knowledge and total ignorance. The levels of uncertainty (ranked according to their proximity to determinacy) are: statistical uncertainty, scenario uncertainty, recognised ignorance and total ignorance. Indeterminacy is located between recognised and total ignorance (Walker et al., 2003).
- Source or location: indicates where the uncertainty manifests itself within the system being studied. The different sources often identified are: input data uncertainty, model uncertainty (including parameter values, model technical aspects, and model structure), context uncertainties (e.g. the boundaries of the system modelled), and multiple knowledge frames (e.g. different perceptions of the problem studied).
- Nature: refers to whether the uncertainty arises due to the imperfection of our knowledge (epistemic uncertainty) or inherent variability (aleatory

uncertainty) of the phenomena studied. Refsgaard et al. (2013) also considered ambiguity as a nature of uncertainty. This represents the uncertainty arising from different ways of understanding or interpreting the system.

These three dimensions of uncertainty are used here to describe the uncertainties in climate change impact studies, where several uncertainties arise from the different steps in the modelling chain. The complete set of uncertainties is often referred to as uncertainty cascade or explosion. This concept illustrates the idea that uncertainty propagates from one level of the modelling chain to the next (e.g. Foley, 2010; Refsgaard et al., 2013; Wilby and Dessai, 2010). Figure 2.1 shows the uncertainty cascade in impact studies adopted here. The uncertainties in the cascade have different characteristics and are addressed differently within impact studies (CCSP, 2009; IPCC, 2007; Foley, 2010; Refsgaard et al., 2013).

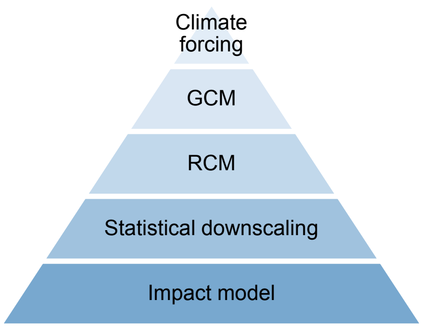

Figure 2.1. Uncertainty cascade in climate change impact studies

Climate forcing scenarios are typically defined by the IPCC and reflect the expert knowledge regarding future emissions of greenhouse gases and aerosols. The two major classes of climate forcing scenarios are the recently suggested Representative Concentration Pathways (RCPs) (Moss et al., 2010) and the emission scenarios defined in the Special Report on Emissions Scenarios (SRES) (Nakićenović, 2000). As its name indicates, the level of this uncertainty is scenario uncertainty, i.e. each scenario is considered as a plausible outcome, but the probabilities of these outcomes are not known. Several sources of uncertainty are present in the definition of a climate forcing. The main ones are: the input data and models used to define the socio-economic scenarios, the context, and the multiple knowledge frames (Refsgaard et al., 2013). Most of these uncertainties arise from the difficulty in foreseen human behaviour, which will define demography, technology, economy, agriculture, etc. (Foley, 2010; Moss et al., 2010). Refsgaard et al. (2013) considered the nature of this uncertainty as mainly ambiguity and partially epistemic (i.e. this uncertainty might be reduced if more knowledge is acquired), while Foley (2010) classified it as also aleatory (irreducible).

In recent years, the level of uncertainty in climate model projections (GCMs or RCMs) has mainly been considered and treated as statistical uncertainty, i.e. it is described using statistical terms and probabilities. The main sources of uncertainty studied are model structure, model technical aspects, and parameter values uncertainties. Model structure uncertainty is generally addressed using multi-model ensembles (e.g. Buser et al., 2009; Leith and Chandler, 2010; Tebaldi et al., 2005), while model technical aspects and parameter values uncertainties are often analysed using perturbed physics ensembles (e.g. Barnett et al., 2006; Murphy et al., 2004; Murphy et al. 2009). The nature of the uncertainty in climate model projections is considered mainly epistemic (Refsgaard et al., 2013).

As in the case of climate model projections, the level and nature of the uncertainty in SDMs are mainly characterised as statistical and epistemic uncertainty, respectively. In addition, the main sources of uncertainty are model structure and parameter values uncertainties (Refsgaard et al., 2013). Contrary to climate model projections, statistical downscaling uncertainty has not yet been quantified in a probabilistic way. Only recent studies have addressed the uncertainty arising from SDMs by comparing a range of methods (e.g. Bürger et al., 2013; Hanel et al., 2013; Räisänen and Räty, 2013; Sunyer et al., 2012; Vrac et al., 2007).

In impact models such as hydrological models, the level of uncertainty is classified as statistical uncertainty. This uncertainty arises from several sources, but primarily parameter values and model structure uncertainties. It is generally considered that this uncertainty could potentially be reduced, i.e. its nature is epistemic. In climate change impact studies and as in the case of SDMs, this uncertainty is rarely analysed using probabilistic procedures. Several studies explore the uncertainty arising from impact models by comparing the results of different model structures and parameterizations (e.g. Dobler et al., 2012; Lawrence and Haddeland, 2011; Wilby and Harris, 2006).

Even though it is not explicitly included in the uncertainty cascade, climate change impact studies are also subject to natural variability. Natural variability is present in the observational data as well as in the climate models (where it is often referred to as internal variability). This uncertainty is by nature aleatory and it is often treated as statistical uncertainty. Several climate change studies have quantified this uncertainty (e.g. Déqué et al., 2012; Deser et al., 2012; Hawkins and Sutton, 2011).

The following sections describe in more detail the uncertainty in RCMs and SDMs, which have been the main focus of this research.

2.2 Regional climate models

As mentioned above, the main sources of uncertainty often studied from RCMs are model technical aspects, parameter values, and model structure uncertainties. Part of the uncertainty in technical aspects and parameter values arises from the use of parameterization schemes. Parameterization schemes are used because small-scale processes, such as convective precipitation, need to be empirically described rather than resolved at the grid scale (Knutti et al 2010). Perturbed physics ensembles have been used in several studies to address the influence of choices of parameterization schemes and their parameter values in both RCMs and GCMs (e.g. Allen, 1999; Barnett et al., 2006; Fowler et al., 2010; van der Linden and Mitchell, 2009; Murphy et al., 2004). These ensembles are obtained by perturbing a subset of uncertain parameters in one climate model.

The uncertainty arising from the existence of alternative structural aspects in RCMs, such as the fundamental assumptions in a parameterization scheme, is addressed as model structure uncertainty (Barnett et al., 2006). This uncertainty refers to the fact that no set of parameters will make a model agree perfectly with observations, because some processes are not or only partially represented in the RCM (Knutti et al., 2010). This uncertainty is commonly studied using multi-model ensembles.

In recent years, coordinated efforts have produced large multi-model ensembles of both GCMs and RCMs. The ensemble from the 5th Coupled Model Inter-comparison project (CMIP5) is currently the largest ensemble of state-of-the-art GCMs (Taylor et al., 2012). Regarding RCMs, the first large European project was PRUDENCE (Christensen et al., 2007). The ENSEMBLES project (van der Linden and Mitchell, 2009) followed the PRUDENCE project and made available a large dataset of state-of-the-art RCMs driven by several GCMs. Currently, the Coordinated Regional climate Downscaling

Experiment[1] (CORDEX) is carrying out RCM simulations for a set of regions covering the majority of populated land regions on the globe. A common goal in ENSEMBLES, PRUDENCE, and CORDEX is the analysis of uncertainties in regional climate projections.

The multi-model ensembles made available from these projects are "ensembles of opportunity", i.e. the models included in the ensembles are those provided by the modelling centres that want to contribute; that is, the models are sampled neither systematically nor randomly (Foley, 2010; Knutti et al., 2010; Tebaldi and Knutti, 2007). In addition, most modelling groups contribute only with their "best" model.

There are two aspects to be considered from "ensembles of opportunity". The first one is that due to the way these ensembles are constructed, they sample several sources of uncertainty. Sources of uncertainty such as technical aspects and parameter values uncertainties are sampled in addition to model structural uncertainty (Knutti et al., 2010). In the case of ensembles of RCMs driven by several GCMs, the uncertainty arising from the choice of GCM is also included.

The second point to be noted is that a multi-model ensemble does not represent the whole range of possible models. Hence, it does not cover the full range of uncertainty that is known to exist (Knutti et al., 2010; Tebaldi and Knutti, 2007). This implies that even though the level of uncertainty often considered is statistical uncertainty, recognized ignorance is also present.

Multi-model ensembles provide the data needed for quantifying the statistical uncertainty in RCMs. In recent years, several probabilistic procedures based on multi-model ensemble techniques have been proposed to address this uncertainty. Räisänen and Palmer (2001) suggested techniques commonly used in weather forecasting to evaluate climate model projections. Since then, several probabilistic procedures have been proposed. For example, the Reliability Ensemble Averaging method suggested by Giorgi and Mearns (2002), the Bayesian methods suggested by Tebaldi et al. (2005), Leith and Chandler (2010), and Buser et al. (2010), and the optimal fingerprinting technique suggested by Allen and Stott (2003). Nonetheless, there are several remaining challenges in the use of multi-model ensembles to quantify statistical uncertainty (Knutti et al., 2010). The main challenges discussed in the literature

[1] http://wcrp-cordex.ipsl.jussieu.fr/

are: the limited number of models in the ensemble, the interdependency between the ensemble members, and the lack of consensus on how to evaluate the performance of the climate models.

The limited number of climate model outputs is related to the discussion on the use of an "ensemble of opportunity". The number of models available is limited (typically between 10 and 30 models) and does not include all possible models. The small number of models in the ensemble also poses a challenge in the use of standard uncertainty quantification techniques.

In studies focusing on extreme precipitation projections for urban hydrology, the limited number of models is an especially important challenge. Currently, large ensembles of RCMs at high spatio-temporal resolution that suit the needs of urban hydrology are not available. This is likely due to the fact that RCM simulations at high spatio-temporal resolution are more computationally demanding in terms of pre- and post-processing needs. The term high spatio-temporal resolution is used here to refer to RCMs with a spatial resolution of approximately 10x10 km^2 and sub-daily temporal resolutions, respectively.

Interdependency in RCM outputs arises, for example, from the fact that some models share part of the code or are driven by the same GCM. The interdependency in GCM outputs has been addressed in a few recent studies (e.g. Jun et al., 2008; Knutti, 2010; Masson and Knutti, 2011; Pennell and Reichler, 2011), but it has not yet been applied to RCMs or included in the uncertainty quantification approaches. The assumption of independency is often used in uncertainty quantification approaches (e.g. Buser et al., 2009; Furrer et al., 2007; Tebaldi et al., 2005), but it may lead to an underestimation of the uncertainty. As discussed in Pennell and Reichler (2011) and Knutti (2010), considering multiple models should only increase our confidence if they are at least partly independent. Despite its potential implications, little attention has been given to address this issue.

The performance of the RCMs depends on the metric used to assess the RCMs, region and climate variable studied (e.g. Christensen et al., 2010; Gómez-Navarro et al., 2012; Kjellström et al., 2010; Lenderink, 2010). The definition of metrics to assess the weights of the RCMs is not trivial (Knutti, 2010; Weigel et al. 2010). Weigel et al. (2010) studied the effects of weighting climate models and highlighted the risk of applying weights. They pointed out that, in addition to accurate knowledge on the performance of the models, model weighting approaches should also take into account the interdependency between the model errors and internal variability. If these aspects are not taken into account the use of weights to combine models might lead to larger errors than equal weighting (Weigel et al., 2010).

Due to lack of information about the future, climate models are often only evaluated according to their performance in current climate conditions. The performance of the models is then assumed to remain unchanged under future conditions. However, a recent study by Boberg and Christensen (2012) has suggested that the performance of climate models might change under future conditions.

Refsgaard et al. (2014) suggested a framework to carry out a more robust assessment of the performance of the RCMs. Their framework aims at assessing the ability of the models to represent climate changes. They suggested the use of differential split-sample tests as a validation methodology. These tests account for the fact that climate conditions are non-stationary and are often carried out using observations for periods with different climate conditions. Refsgaard et al. (2014) recommended the use of non-stationary data sets to perform differential split-sample tests.

The nature of the uncertainty in climate model projections is mainly considered epistemic, i.e. reducible if more knowledge becomes available, and partly aleatory due to internal variability. However, it must be highlighted that in the context of climate change more knowledge might not necessarily reduce the epistemic uncertainty. Instead, more knowledge might reveal unforeseen complexities in the climate system and new uncertainties (Curry and Webster, 2011; van der Sluijs, 2005).

The uncertainty investigated in this thesis from the RCMs is the statistical uncertainty in a multi-model ensemble, which is an "ensemble of opportunity". Hence, the source of uncertainty sampled is mainly model structure uncertainty, but model technical aspects and parameter values uncertainties are also implicitly sampled. The presence of the other sources and levels of uncertainty described in this section are acknowledged, as well as the possible unknown unknowns (total ignorance), which cannot be foreseen. However, these uncertainties are not investigated here.

2.3 Statistical downscaling

The two main sources of uncertainty in statistical downscaling are model structure and parameter values uncertainties. Model structure uncertainty arises from the existence of a large number of SDMs based on different underlying assumptions. Parameter values uncertainty arises due the lack of knowledge on the right value of the parameters to obtain information on a climate variable under future conditions.

The SDMs suggested in the literature and the SDMs commonly used in hydrological applications are reviewed in detail by Maraun et al. (2010) and Fowler et al. (2007). Currently, there is no consensus on the “best” SDM. This is due to the difficulty in validating the different methods and the fact that different applications have different needs (Fowler et al., 2007; Maraun et al., 2010).

One common assumption to all SDMs, which is difficult to verify, is that the bias of the RCMs will remain constant, see discussion in e.g. Teutschbein and Seibert (2013) and Ehret et al. (2012). This assumption adds parameter values uncertainty to SDMs, in addition to the parameter values uncertainty present in all environmental modelling approaches (Refsgaard et al., 2007). Even if a best set of parameter values can be found for current conditions, this might not be suitable for representing future climate conditions. Parameter values cannot be validated due to the lack of observations representing the future.

As in the case of RCMs, the use of differential split-sample tests is a way in which the robustness of the SDMs can be evaluated with respect to their ability to represent future climate conditions (Refsgaard et al., 2014). Only very few studies have used differential split-sample tests to evaluate the performance of SDMs (e.g. Teutschbein and Seibert, 2013). Another approach to assess the performance of the SDMs under current and future climate conditions is the use of cross-validation techniques. A few recent studies have used these techniques to assess SDMs, see e.g. Räisänen and Räty (2013) and Vrac et al. (2007). These cross-validation strategies are based on the evaluation of SDMs using pseudo-realities (defined using multi-model ensembles of RCMs).

Fowler et al. (2007) suggested the use of a range of SDMs, especially in applications where the main focus is on extreme events. However, most climate change impact studies apply just one method. Recent studies have acknowledged the uncertainty in statistical downscaling and used several methods (e.g. Bürger et al., 2013; Hanel et al., 2013; Teutschbein et al., 2011). In these studies, the outputs from the different methods are either presented separately or joined using, for example, the average and variability of the outputs from the different SDMs. Probabilistic procedures based on an ensemble of SDMs similar to the procedures used for climate models have not yet been suggested.

The source of uncertainty in statistical downscaling explored in this thesis is model structure uncertainty. Other sources of uncertainty, such as the input data and parameter values uncertainty are not addressed here. Additionally, as in the case of the uncertainty in RCMs, the presence of recognised and total ignorance is acknowledged, but it is out of the scope of this study.

3 Data and case studies

Denmark is the main study area considered in this research. It was used in the evaluation of RCMs (Paper **I** to **III**) and SDMs for urban hydrology (Paper **V**). Eleven European catchments were considered in the evaluation of SDMs for river hydrology (Paper **IV**), which was carried out within the COST Action FloodFreq[2].

Two types of data were used in all the analyses: observational data and RCM outputs. Four precipitation observational data sets were considered in the studies focusing on Denmark, these are: Spildevandskomitéens regnmålersystem (SVK), Climate Grid Denmark (CGD), European Climate Assessment and Dataset (ECA&D), and E-OBS. The SVK and ECA&D data sets are point measurements, while CGD and E-OBS are gridded data sets. Their main characteristics are:

- SVK consists of one-minute temporal resolution records for approximately 100 stations in Denmark. The network is operated by the Water Pollution Committee of The Society of Danish Engineers and the Danish Meteorological Institute (DMI). It is primarily designed for measuring high intense precipitation events and uses a rather high threshold for dry weather, i.e. hours with less than approximately 0.2–0.4 mm are considered dry (Jørgensen et al., 1998).
- CGD has a spatial resolution of 10x10 km and it is based on approximately 300 stations over Denmark (Scharling, 2012). Both the station and gridded data have been extensively studied and quality checked by DMI (Scharling and Kern-Hansen, 2002).
- ECA&D is a large pan-European station data set that contains more than 2000 stations measuring daily precipitation (Klein Tank et al., 2002; Klok and Klein Tank, 2009). In Denmark, there are a total of 26 stations of which 17 are available for downloading.
- E-OBS is based on ECA&D (Haylock et al., 2008). The gridded data at a resolution of 0.22º (approximately 25 km) has been used here. It should be pointed out that the low station density of ECA&D over Denmark might lead to over-smoothing of precipitation intensities in E-OBS (Hofstra et al., 2009, 2010).

[2] European COST Action ES0901, http://www.cost-floodfreq.eu/

The observational data used from the eleven European catchments are daily catchment precipitation time series. These were estimated from either point measurements or gridded data sets depending on the catchment. More details on all the observational data sets can be found in Paper **II** and **IV**.

The climate model outputs used in this research are an ensemble of fifteen RCM simulations driven by several GCMs from the ENSEMBLES project (van der Linden and Mitchell, 2009). This ensemble includes eleven RCMs and six GCMs. In addition, the ensemble of the eleven RCMs run using the re-analyses data ERA-40 as boundary conditions was analysed in Paper **I**.

The RCMs have a spatial and temporal resolution of 0.22º (approximately 25 km) and 1 day, respectively. Nine RCMs use the same rotated pole grid system, while two models (RM5.1 and RegCM) use a Lambert conformal grid system. All the models are driven by the emission scenario A1B from SRES (Nakićenović, 2000). The RCMs considered are shown in Table 3.1.

Table 3.1. List of RCMs and driving GCMs used. The first two columns indicate the number given to each RCM in Paper **I** and **II**.

No. (Paper **II**)	No. (Paper **I**)	RCM	GCM
1	10f	HIRHAM5	ARPEGE
2	10a	HIRHAM5	ECHAM5
3	10b	HIRHAM5	BCM
4	4a	REMO	ECHAM5
5	2a	RACMO2	ECHAM5
6	3a	RCA	ECHAM5
7	3b	RCA	BCM
8	3c	RCA	HadCM3Q3
9	6e	CLM	HadCM3Q0
10	7e	HadRM3Q0	HadCM3Q0
11	8c	HadRM3Q3	HadCM3Q3
12	9d	HadRM3Q16	HadCM3Q16
13	5d	RCA3	HadCM3Q16
14	1f	RM5.1	ARPEGE
15	11a	RegCM3	ECHAM5

In order to compare the different data sets, the precipitation indices estimated for the two RCMs using the Lambert conformal system were re-interpolated to the rotated pole grid system. This was done using natural neighbour interpolation (Sibson, 1980; 1981). Additionally, the CGD data set was also re-interpolated into the same rotated pole grid system as the RCMs; the re-interpolated data set is referred to as CGD-25.

4 Uncertainty in regional climate model projections

This chapter presents the analyses of the statistical uncertainty in extreme precipitation projections from the ensemble of RCMs. It is divided in two sections. The first section addresses three aspects from the ensemble of RCMs relevant for the analysis of the uncertainty. These are: the interdependency of RCM outputs, the performance of the RCMs under current climate conditions, and the changes in the performance under future climate conditions. The second section presents an uncertainty quantification approach, which takes into account the findings from the first section.

4.1 Evaluation of a multi-model ensemble

4.1.1 Interdependency of RCMs

The interdependency of the RCMs refers to the fact that some models have been constructed in a similar way, i.e. some models share parts of the code, use the same parameterization schemes, have been developed at the same centre, and/or are driven by the same GCM. How to estimate it and take it into account is one of the challenges in combining outputs from multiple climate models (Knutti, 2010; Knutti et al., 2010).

It is considered that two RCMs are not independent because they produce different results, but because they reach them using different paths (Pennell and Reichler, 2011). This could be analysed from the description of the physical processes, initial conditions, boundary conditions, etc., in the RCMs or using statistical methods to analyse the RCM outputs. The analysis of the characteristics of the models in ENSEMBLES is difficult because a comprehensive description of the RCMs is not available. Thus, this study focuses on the use of statistical methods.

Pennell and Reichler (2011) suggested two statistical methods to estimate the amount of independent information in the ensemble of GCMs from CMIP3 (Meehl et al., 2007). In this study, these methods were applied to the RCMs from ENSEMBLES for a set of precipitation indices.

Four precipitation indices are considered here: mean precipitation, mean precipitation amount per wet day (precipitation higher or equal to 1 mm) referred to as simple daily intensity index (SDII), and the 95th and 99th percentile of wet days precipitation amount referred to as $RR_{wn}95$ and $RR_{wn}99$, respectively. These indices are included in the list of indices recommended for the analysis of changes in extreme events; see STARDEX (Haylock and Goodess, 2004) and ETCCDI (Peterson, 2005). The indices $RR_{wn}95$ and $RR_{wn}99$ are sometimes also referred to as Prec95p and Prec99p. A larger set of indices are included in Paper **I**.

The two methods suggested by Pennell and Reichler (2011) are the EIGEN and Z method. These methods use known statistical techniques to estimate the effective number of climate models, which is defined as the amount of statistically independent information in the ensemble.

The EIGEN and Z methods are based on a metric, d. This metric is a measure of the RCM's error in representing current climate conditions. For each index, it is estimated using the standardised individual model error and ensemble average error. The individual model error is estimated by subtracting the observations from the RCM outputs and dividing by the inter-annual variability of the observations. The ensemble average error is the average of all the model errors and represents the common biases in the RCMs. The metric is then calculated by removing the part of the ensemble average error present in the individual model error.

The EIGEN method is based on the eigenanalysis of the correlation matrix, $\mathbf{R}$. Each element of this matrix is the correlation between the values of d obtained for all the grid points for two RCMs. The eigenvalues of $\mathbf{R}$ are used to estimate the effective number of climate models, $\hat{M}_{eff,E}$, as (Bretherton et al., 1999; Pennell and Reichler, 2011):

$$\hat{M}_{eff,E} = \frac{\left(\sum_{m=1}^{M} \lambda_m\right)^2}{\sum_{m=1}^{M} \lambda_m^2} \tag{1}$$

where λ_m is the eigenvalue of the RCM m and M is the total number of RCMs in the ensemble. The correction suggested by Bretherton et al. (1999) is then applied to take into account the influence of the limited number of RCMs in the ensemble. See Paper **I** for more details.

The Z method is based on known properties of the Fisher's z transformation of correlation coefficients (Wang and Shen, 1999; Wilks, 2006). This method first estimates the correlation between the values of d obtained for all the RCMs for two grid points. The Fisher's z transformation is then calculated for all the pairs of grid points separated by a distance larger than the decorrelation length. The Fisher's z transformation is used to estimate the effective number of climate models, $\hat{M}_{eff,Z}$, as:

$$\hat{M}_{eff,Z} = \left[\frac{1}{K-1} \sum_{i<j} \left(z_{ij} - \bar{z} \right)^2 \right]^{-1} + 3 \qquad (2)$$

where z_{ij} is Fisher's z transformation obtained for the grid points i and j, K is the total number of pairs of grid points considered, and $\bar{z}$ is the average of all the values of z_{ij}.

In addition to the EIGEN and Z methods, a hierarchical cluster analysis was carried out to assess the structure of the similarities in the RCMs. The clustering approach groups the RCMs with a higher degree of similarity based on the idea of distance (Wilks, 2006). In this study, the distance between the RCMs was defined as 1- **R**.

The EIGEN method, Z method, and the hierarchical analysis were applied to the ensemble of RCMs driven by ERA-40 and the ensemble of RCMs driven by GCMs. The observational data set used is E-OBS and the time period considered is 1961–1990. The main results obtained for the RCMs driven by GCMs are described here. A detailed description of the methods and results can be found in Paper **I**.

Table 4.1 compares the effective number of RCMs obtained for the EIGEN and Z methods for winter (December–February), summer (June–August), and without dividing into seasons (referred to as annual). Most of the results in this and the following Chapter are shown for winter and summer. This allows us to discuss the differences in the results depending on the season as well as to study both frontal and convective precipitation events. Convective storms occur more frequently in summer, while winter extremes are mainly caused by frontal storms.

For all the indices and both methods, the effective number of RCMs is smaller than the ensemble size. However, there are large differences (approximately 4 effective number of models) between the results obtained from the EIGEN and Z method. The difference between the two methods might be influenced by the uncertainty in the results of the Z method. The results of this method are affected by the sampling error in the estimation of the correlation between two relatively short vectors (the length of the vectors is equal to M) and the definition of the decorrelation length.

Table 4.1. Effective number of climate models estimated from the EIGEN and Z methods for four precipitation indices. Adapted from: Paper **I**.

	WINTER		SUMMER		ANNUAL	
Indices	EIGEN	Z	EIGEN	Z	EIGEN	Z
Mean	5.5	7.9	4.9	9.0	4.7	8.1
SDII	6.5	9.8	7.1	11.9	6.5	8.9
$RR_{wn}95$	5.9	9.1	6.6	12.6	6.2	9.0
$RR_{wn}99$	7.9	12.6	7.7	12.9	7.6	14.3

Different ensemble sizes were considered to further assess the effective number of RCMs. Figure 4.1 shows the effective number of RCMs as a function of the ensemble size estimated using 500 bootstrap samples. The figure shows the results for the mean and $RR_{wn}95$ for the EIGEN method (similar results were obtained for the Z method). For both indices and the three periods the effective number of climate models is lower than the ensemble size for all the ensemble sizes.

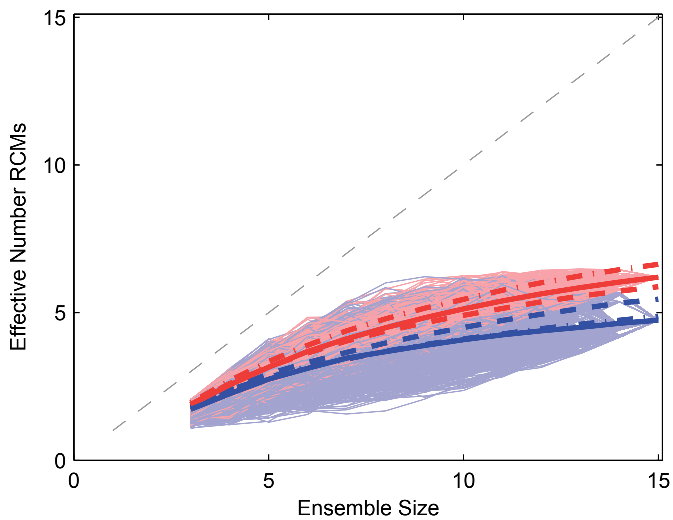

Figure 4.1. Effective number of RCMs vs. ensemble size for the mean (in blue) and $RR_{wn}95$ (in red) estimated using the EIGEN method. The thick solid lines show the average of the 500 bootstrap samples and the semi-transparent lines show each of the samples for the annual period. The dashed and dash-dot lines show the averages for winter and summer, respectively. Source: Paper **I**.

The slope of the curves decreases as the ensemble size increases. This indicates that as the ensemble size increases, the amount of independent information added by including outputs from one more RCM decreases. Nonetheless, the curves do not converge to a constant level, which indicates that all the RCMs in the ensemble contribute with some new information.

Figure 4.2 shows the dendrograms obtained from the cluster analysis for the mean and $RR_{wn}95$. The y-axis in the dendrograms indicates the dissimilarity of the RCMs and the x-axis shows all the RCMs in the ensemble (see Table 3.1 for the numbering used for each RCM).

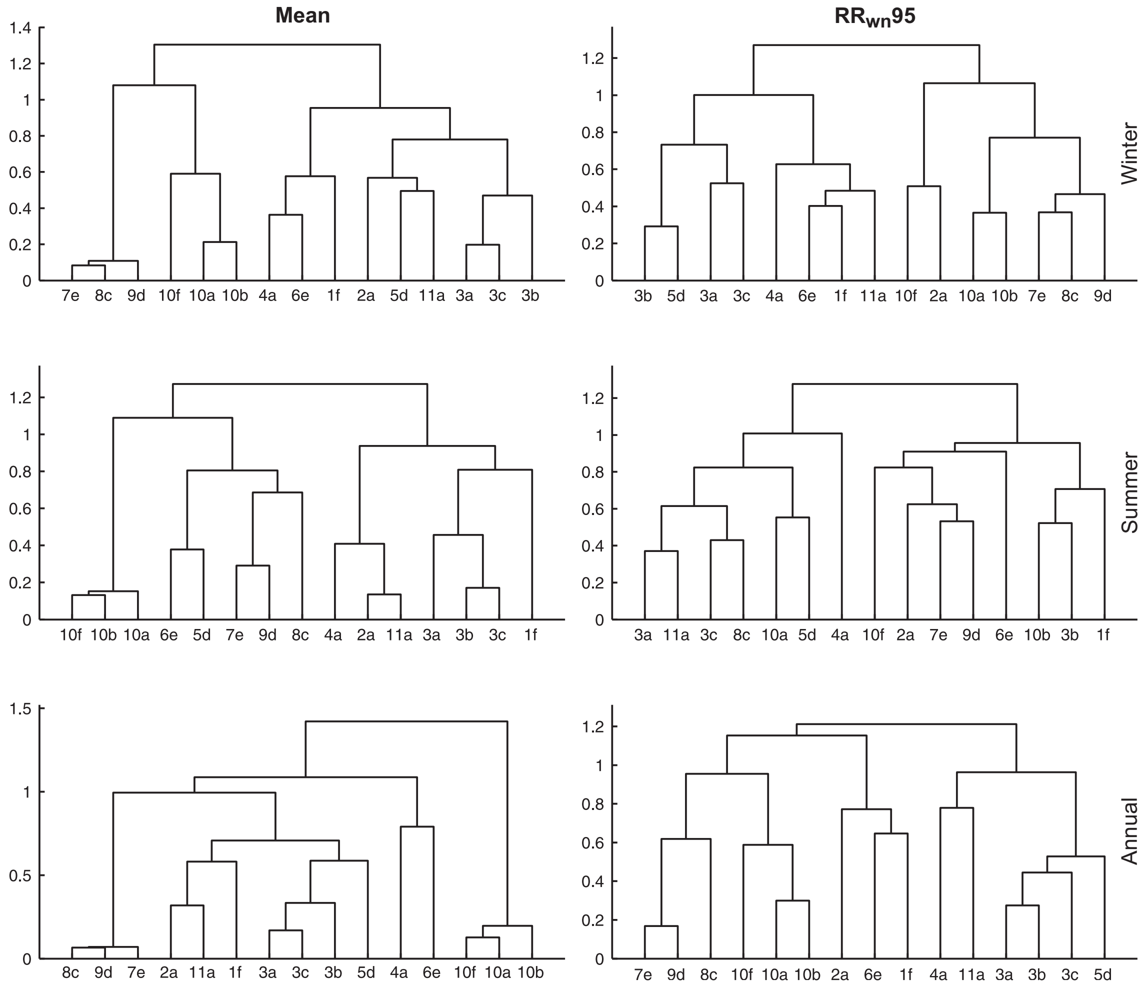

Figure 4.2. Dendrograms for the mean (left) and $RR_{wn}95$ (right) for winter (top), summer (middle) and annual period (bottom). The y-axis indicates the dissimilarity of the climate models. The numbering used for each RCMs is shown in Table 3.1. Source: Paper **I**.

For mean precipitation and for all the three periods, the outputs from the same RCM driven by different GCMs (i.e. HIRHAM5 (models 10), RCA (models 3) and HadRM3 (models 7, 8 and 9)) are grouped in the same cluster and have a relatively high similarity. For $RR_{wn}95$, these clusters are only partly identified for the winter and annual period, whereas for summer there is not a clear grouping of the RCMs.

In addition, for both the mean and $RR_{wn}95$ there is not a clear grouping of different RCMs driven by the same GCM. The influence of using the same GCM is only slightly noticeable for mean precipitation. For example, for all three periods, the models RACMO2 and RegCM3 driven by ECHAM5 (models 2a and 11a) form a cluster with higher or comparable similarity than the clusters formed by the HIRHAM5, HadRM3 and RCA models. This is not observed in the dendrograms for $RR_{wn}95$. It must be noted that the results of the hierarchical analysis should be treated with care as they might be influenced by biases in the observational data set (see a comparison of the results obtained using E-OBS and CGD-25 as observational data sets in Paper **II**).

The results from the EIGEN method, Z method and hierarchical analysis confirm that the RCMs cannot be considered independent. In addition, the hierarchical analysis showed that a larger part of the interdependency is caused by the use of the same RCM driven by different GCMs rather than by the use of the same GCM to drive different RCMs.

4.1.2 RCMs performance under current climate

Most studies addressing the uncertainty in multi-model ensembles assess the performance of the climate models to define some sort of weighting approach (e.g. Lenderink, 2010; van der Linden and Mitchell, 2009; Tebaldi et al., 2005). However, there is no consensus on what is a good or a bad model (Knutti et al., 2010; Tebaldi and Knutti, 2007).

Several studies evaluate the ability of the RCMs to simulate precipitation (e.g. Boberg et al., 2010; Fowler and Ekström, 2009; Lenderink, 2010). Due to the lack of observations for the future, this is commonly done by comparing the RCM outputs for current conditions to observations. These studies use different observational data sets, indices, and metrics. Paper **II** includes a review of the different approaches used in the literature.

This section focuses on the ability of the RCMs to simulate precipitation over Denmark under current climate conditions. It describes the performance of the RCMs considering four observational data sets, four indices, and two metrics.

The observational data sets considered are: SVK, CGD-25, ECA&D, and E-OBS, which represent the common types of observational data sets used in climate change impact studies, i.e. point measurement and gridded data. The time period common to all the observations was considered, this is 1989–2010.

The precipitation indices used are the same as in the previous section, i.e. mean precipitation, SDII, $RR_{wn}95$, and $RR_{wn}99$. These indices were calculated for each point measurement and grid point in the observational data sets and the RCMs. In addition, empirical semivariograms were estimated for each index for the observational gridded data sets (CGD-25 and E-OBS) and the RCMs. Empirical semivariograms provide a measure of how the similarity between grid points (semivariance) changes with distance. The indices for each grid point and semivariance were estimated without dividing the year into seasons.

The performance of the RCMs was then estimated for each index using two metrics. The first metric is based on the bias of the RCMs at each grid point. It is calculated in two steps. First the bias is calculated by subtracting the observations from the RCM output, i.e. a positive bias indicates that the RCM overestimates the observations. Then the median of the bias for all grid points is estimated and the metric is defined as the absolute value of the median. The RCMs were ranked according to this metric. The RCM leading to the smallest value of the metric was ranked in first position.

The second metric is based on the ability of the RCMs to represent the spatial variability of the observations. For this purpose, the empirical semivariograms estimated from the RCMs are compared to those estimated from the observations using the Root Mean Square Error (RMSE). The RCMs were also ranked according to this metric. The RCM with the smallest RMSE were ranked in first position. See Paper **II** for a detailed description of the indices and the metrics.

The main findings of this analysis are described using the results found for the bias and the rankings of the RCMs. A detailed description of all the results can be found in Paper **II**.

Figure 4.3 shows the median of the bias found for each RCM. For all the indices, the bias depends on the observational data set considered. In the case of the mean precipitation and for most RCMs, the observations agree on the positive sign of the bias but disagree on the magnitude. For the other indices the observations disagree on both the sign and the magnitude of the bias. In general, SVK, CGD-25, and ECA&D point to an underestimation by the

RCMs of the indices representing extreme precipitation properties, while E-OBS points to an overestimation. These differences in the bias arise from the differences in the properties of the observational data sets, such as the smoothing of extreme precipitation in E-OBS; see the analysis of the observational data sets in Paper **II**.

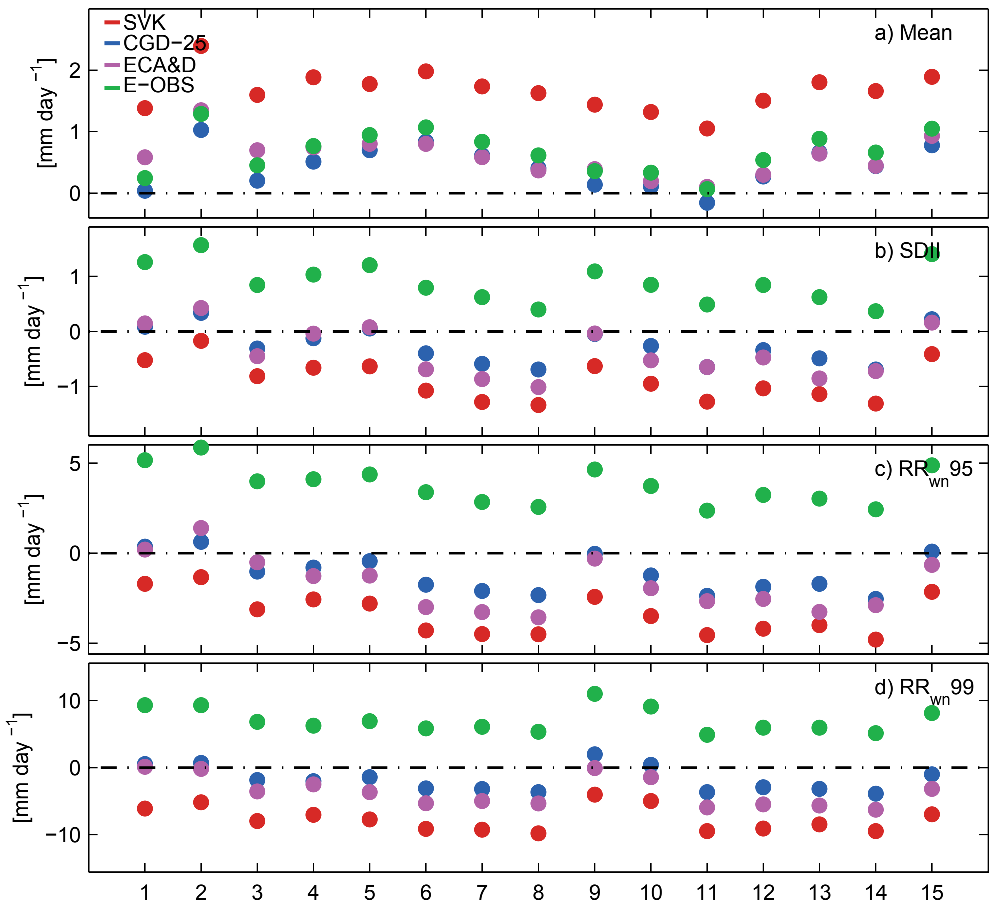

Figure 4.3. Median of the bias for all the RCMs for four indices and four observational data sets. The numbering used for each RCMs is shown in Table 3.1. Source: Paper **II**.

For the same observational data set, the bias depends on the index considered. For example, in the case of CGD-25, most RCMs overestimate mean precipitation but underestimate extreme precipitation properties. As expected, higher biases were found for higher precipitation intensities.

The relevance of the differences in the bias estimated for the different observational data sets and indices is clearer from the ranking of the RCMs. Table 4.2 shows the ranking of the RCMs according to the two metrics, two indices (mean and $RR_{wn}95$), and two observational data sets (CGD-25 and E-OBS). The main point to highlight from these rankings is that the position of the RCMs depends on the metric, index, and observational data set considered.

In the case of the mean and for both metrics, the rankings are virtually identical for CGD-25 and E-OBS, but this is not the case for $RR_{wn}95$. For $RR_{wn}95$ and the metric representing the bias, the RCMs ranked in the first positions are almost opposite for the two observational data sets (e.g. model 9 and 11). For the metric representing the spatial variability, different RCMs are also ranked in the first positions for the two observational data sets, but the overall ranking is more similar than for the metric representing the bias.

Table 4.2. Ranking of the RCMs considering the observational data sets: CGD-25 and E-OBS; the indices: mean and $RR_{wn}95$; and the metrics for the bias and spatial variability. The numbering used for each RCMs is shown in Table 3.1. For comparison, the RCMs in the first five positions for the bias of the mean are highlighted in grey in all the columns. Adapted from: Paper **II**.

	BIAS GRID POINT				RMSE SPATIAL VARIABILITY			
	Mean		$RR_{wn}95$		Mean		$RR_{wn}95$	
Ranking	CGD-25	E-OBS	CGD-25	E-OBS	CGD-25	E-OBS	CGD-25	EOBS
1	1	11	9	11	5	5	12	5
2	10	1	15	14	1	1	3	2
3	9	10	1	8	12	2	1	6
4	11	9	5	7	2	12	11	4
5	3	3	2	13	11	4	15	3
6	12	12	4	12	3	11	10	12
7	8	8	3	6	4	3	14	15
8	14	14	10	10	15	15	9	14
9	4	4	13	3	7	7	2	11
10	7	7	6	4	10	10	5	9
11	13	13	12	5	6	6	6	10
12	5	5	7	9	9	9	7	1
13	15	15	8	15	14	13	8	7
14	6	6	11	1	13	14	13	8
15	2	2	14	2	8	8	4	13

For the same observational data set and metric, different RCMs are ranked in the first positions depending on the index considered. Similarly, for the same observational data set and index, different rankings were obtained depending on the metric.

These results illustrate the challenge in identifying a single best or worst model. The combination of the rankings shown in Table 4.2 with the purpose of estimating weights for the RCMs is not straightforward. Moreover, one additional difficulty to defining weights is how to take into account the interdependency of the RCMs. As suggested by Weigel et al. (2010), the interdependency of the RCMs must be taken into account to avoid obtaining biased weights.

The results of this study also show that, for extreme precipitation, the choice of observational data set largely influences the conclusions from the assessment of the RCMs' performance. This highlights the need to compare the RCMs to quality-checked observational data sets that represent the same precipitation characteristics as the RCMs. Here, CGD-25 is the data set that best fits these requirements.

4.1.3 Changes in bias under future climate conditions

The previous section addresses the performance of the RCMs under current climate conditions. This section focuses on the fact that the performance of the RCMs might not be stationary, i.e. it might change under future climate conditions. A few recent studies, such as Refsgaard et al. (2014) and Boberg and Christensen (2012), have addressed this issue.

Boberg and Christensen (2012) suggested a procedure to assess possible changes in bias in monthly mean temperature under future climate conditions. They related the bias of the RCMs driven by ERA-40 re-analysis data to the observed temperature. A similar approach was used in this study to explore possible changes in the biases in extreme precipitation. The procedure suggested here uses the index $RR_{wn}95$ estimated from the RCMs driven by GCMs and it is based on two main steps.

In the first step, for each season s, grid point i, and model m, the bias of the RCMs, $ABias_{i,m,s}$, is estimated as in the previous sections, i.e. $X_{m,i,s} - X_{Obs,i,s}$, where $X_{m,i,s}$ and $X_{Obs,i,s}$ refer to the value of $RR_{wn}95$ estimated from the RCM outputs and the observations, respectively.

In the second step, for each season, a linear regression is estimated between $\mathbf{ABias}_{\cdot,\cdot,s}$ and $\mathbf{X}_{\mathbf{Obs},\cdot,s}$, i.e. between the biases estimated for all the RCMs and the observed values for all the grid points. This approach assumes that the same regression is valid for all the RCMs. The observational data set used in is CGD-25 and the time period considered is 1989–2010. The seasons used are the same as in section 4.1.1. More details on this method can be found in Paper **III**.

Figure 4.4 shows the linear regression found for winter, summer, and annual period. For comparison purposes, the figure also shows the linear regressions fitted to each of the RCMs individually. For all three periods, the linear regressions point towards a decrease and a shift in the sign of the bias for increasing $RR_{wn}95$, especially for summer. In general, the intercept of the linear regression varies depending on the RCMs, but the slope is similar in all the RCMs.

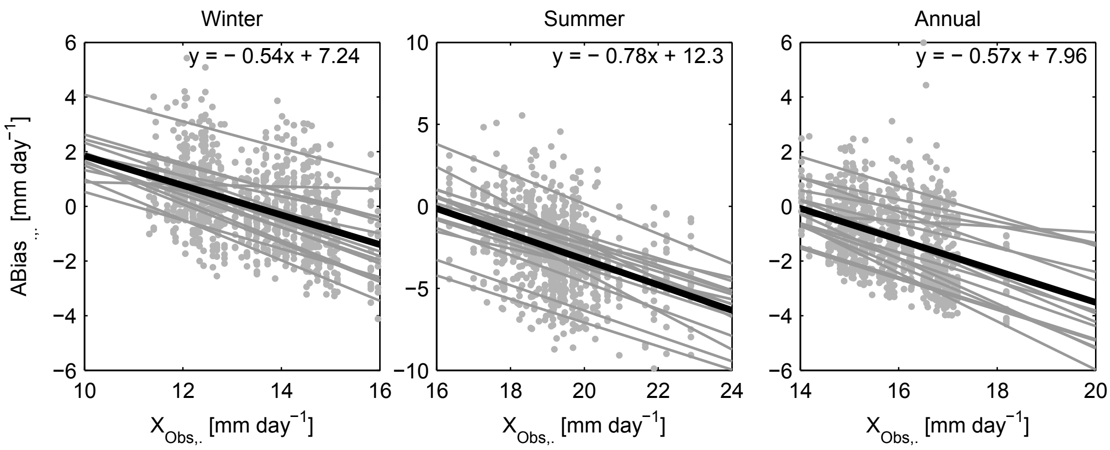

Figure 4.4. Linear regression between the bias and the observations for winter, summer, and annual period. The grey lines show the linear regressions fitted to each RCM individually, the black lines show the linear regressions fitted considering the biases of all the RCMs together. The dots show the values estimated for all grid points and all RCMs. Source: Paper **III**.

This results show that if extreme precipitation is expected to change under future climate conditions, then the bias can also be expected to change. Hence, the assumption of constant bias often used in climate change impact studies might not be valid.

4.2 Uncertainty quantification

The previous section provides insight on some of the challenges in combining RCM outputs from a multi-model ensemble. This section describes the development of an uncertainty quantification approach which takes into account the findings from the previous section. This approach is based on Bayesian statistics and quantifies the statistical uncertainty in extreme precipitation projections. This section focuses on the uncertainty in the index $RR_{wn}95$ under current (1989–2010) and future (2081–2100) climate conditions.

This section is divided into two parts. First the Bayesian approach is introduced and the main results from the approach are presented. Then this approach is used to describe the influence of two assumptions: independency and constant bias of the RCMs.

4.2.1 Bayesian approach

The approach suggested here is inspired by the approaches presented by Tebaldi et al. (2005, 2004) and Buser et al. (2010, 2009). The main difference between their approaches and this one is the incorporation of the interdependency of the RCMs.

The selection of Bayesian inference implies that probabilities are interpreted as the degree of (subjective) belief on the occurrence of an uncertain event (Wilks, 2006). This is in agreement with the definition of uncertainty adopted in this research (see section 2.1) and it is considered a natural way to represent uncertainty in the context of climate change projections (Tebaldi et al., 2005 and Paper **III**). Following Bayes' rule the conditional probability of a set of parameters, $\mathbf{\Theta}$, depending on the data, $\mathbf{D}$, can be expressed as:

$$p(\mathbf{\Theta}|\mathbf{D}) \propto p(\mathbf{\Theta})p(\mathbf{D}|\mathbf{\Theta}) \tag{3}$$

where $p(\mathbf{\Theta}|\mathbf{D})$ is the posterior distribution, $p(\mathbf{\Theta})$ is the prior distribution and $p(\mathbf{D}|\mathbf{\Theta})$ is the likelihood function.

The set of parameters considered here are the parameters of a statistical model. This statistical model is constructed based on the data available and on the assumption that the values of $RR_{wn}95$ estimated from the observations (CGD-25) and the RCMs are normally distributed. The statistical model can be expressed using two multivariate and one univariate normal distribution as:

$$\begin{aligned} &\mathbf{X} \sim N_M\left((\mu+\beta)\mathbf{1}, \lambda^{-1}\mathbf{R}\right) \\ &\mathbf{Y} \sim N_M\left((\nu+\alpha\beta)\mathbf{1}, (\theta\lambda)^{-1}\mathbf{R}\right) \\ &X_{Obs} \sim N\left(\mu, \sigma_{Obs}^2\right) \end{aligned} \tag{4}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are vectors of length M (total number of RCMs) containing the average $RR_{wn}95$ over Denmark estimated from each RCM outputs for current and future conditions, respectively; X_{Obs} is the average and $\sigma_{Obs}{}^2$ the variance of $RR_{wn}95$ estimated from the observations; $\mathbf{R}$ is the correlation matrix of the RCMs assumed to be constant from present to future; μ and ν are scalars that represent the "true mean" of $RR_{wn}95$ for current and future conditions, respectively; β and λ are scalars representing, respectively, the common bias and the reliability (inverse of the variance) of the RCMs for current conditions; α and θ account for the fact that the bias and the reliability might change from present to future. It must be noted that this statistical model relies on a number of subjective assumptions such as the common bias used for all the RCMs and the constant interdependency of the RCMs from present to future, see discussion about the assumptions in the statistical model in Paper **III**.

The results of the previous section are included in the statistical model as: (i) here the elements of **R** are the absolute value of the elements in the matrix defined in the EIGEN method in section 4.1.1; (ii) equal weighting is used for the RCMs, i.e. a common reliability is used for all the RCMs; (iii) α is estimated from the linear regressions defined in section 4.1.3.

The likelihood function is obtained from the multiplication of the three probability density functions in Eq. (4). The prior distribution can be expressed as the product of the marginal prior distributions of all the parameters. These are chosen based on the natural conjugate prior families of the likelihood distributional forms, i.e. normal distributions for μ, v, and β; and gamma distributions for λ and θ. The hyperparameters are chosen to ensure that the priors carry little information.

Once the likelihood and priors are defined, a Markov Chain Monte Carlo (MCMC) algorithm is applied using Gibbs sampling to infer the posterior distribution (Gelman et al., 2003). More details on the Bayesian approach can be found in Paper **III**.

The main output of the Bayesian approach is the posterior distributions of the parameters. Figure 4.5 shows these distributions for winter, summer, and annual period. The values of $RR_{wn}95$ estimated from each of the RCMs and from the observations are shown together with the posterior distributions of μ and v.

The posterior distribution of μ is sharp compared to the individual values from the RCMs. This is caused by the fact that σ_{Obs} (which ranges from 0.14 to 0.39 mm day^{-1} for the three periods) is considerably smaller than the spread of the RCMs. Conversely, all the values of the RCMs are encompassed in the posterior distribution of v. This is a combined effect of the fact that σ_{Obs} does not influence this parameter and that all the RCMs have the same weight.

In agreement with the differences between X_{Obs} and **X**, the bias, β, is centred on approximately 0 mm day^{-1} in winter, while it is negative and centred on approximately -2.3 mm day^{-1} for summer and -1.9 mm day^{-1} for the annual period. In addition, for these two periods the uncertainty in this parameter is considerably larger than for winter. This is likely due to the larger inter-model differences between the RCM outputs for the present and future time periods.

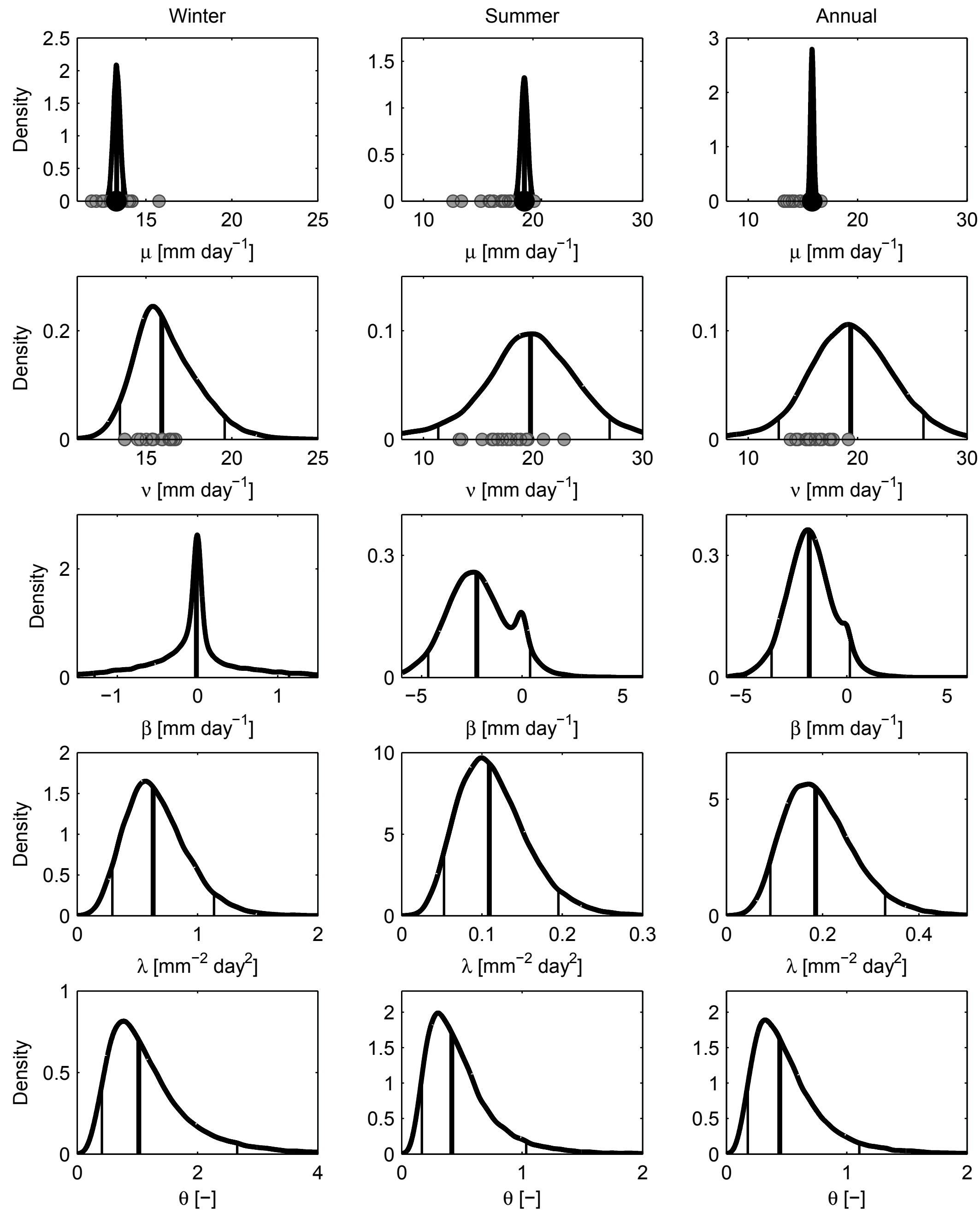

Figure 4.5. Posterior probability density functions of the five parameters in the model (μ, ν, β, λ, and θ) for winter, summer, and annual period. The grey dots are the outputs from each of the RCMs and the black dots are the values estimated from the observations. The vertical thick dashed lines represent the median, while the solid thin lines represent the 5^{th} and 95^{th} percentiles. Adapted from: Paper **III**.

The distributions of λ indicate that the RCMs are more reliable for winter period (larger λ) than for summer and annual periods. In addition, the uncertainty in λ is smaller for summer and annual periods, which shows that there is a higher confidence in the lower reliability of the RCMs for these two periods. The reliability of the RCMs is not estimated to change for winter (the median of θ is equal to 1), but the results show a decrease in the reliability of the RCMs for summer and annual period (the medians of θ are approximately 0.4 for both periods). As in the case of λ, the uncertainty in θ is lower for summer and annual periods than for winter. Similarly to the results found for β, the low reliability of the RCMs and its decrease in the future period for summer and annual periods is caused by the larger inter-model differences in the RCMs.

A detailed analysis of this figure and additional results from the Bayesian approach, such as the analysis of the correlation between the parameters, can be found in Paper **III**.

4.2.2 Effects of interdependency and change in bias

This section describes the results of applying the Bayesian approach to assess the influence of assuming independency and constant bias. This is illustrated using three tests based on different assumptions. These are: (1) the RCMs are independent and the bias constant; (2) the RCMs are interdependent and the bias constant; (3) the RCMs are interdependent and the bias changes from present to future (the results shown in Figure 4.5 correspond to this test). The main output analysed from these tests is the relative change in $RR_{wn}95$ from present to future. This change is referred to as change factor (CF) and it is defined as: CF = ν/μ.

Figure 4.6 shows the posterior distributions of μ, ν, and CF for the three tests. For winter, summer, and annual periods, the distribution of μ is similar for the three tests. This is caused by the large influence of σ_{Obs} in the distribution of μ. This is not the case for ν and CF, which are largely influenced by the assumptions in the tests.

The uncertainty in ν is larger in the tests accounting for the interdependency of the RCMs (tests (2) and (3)). This is due to the fact that less independent information is considered in these tests. The uncertainty in ν is also larger for the test accounting for change in bias (test (3)) than in the tests assuming constant bias (tests (1) and (2)). This is caused by an increase in the uncertainty of the bias for the future period in test (3).

In winter and annual periods, the median of v is larger in the test accounting for change in bias due to a more negative bias in the future period. In summer, the median of v is not affected by the assumption of constant bias since the bias for the future is similar to the bias for the present. The same differences between the three tests described for v are also seen in the distributions of CF.

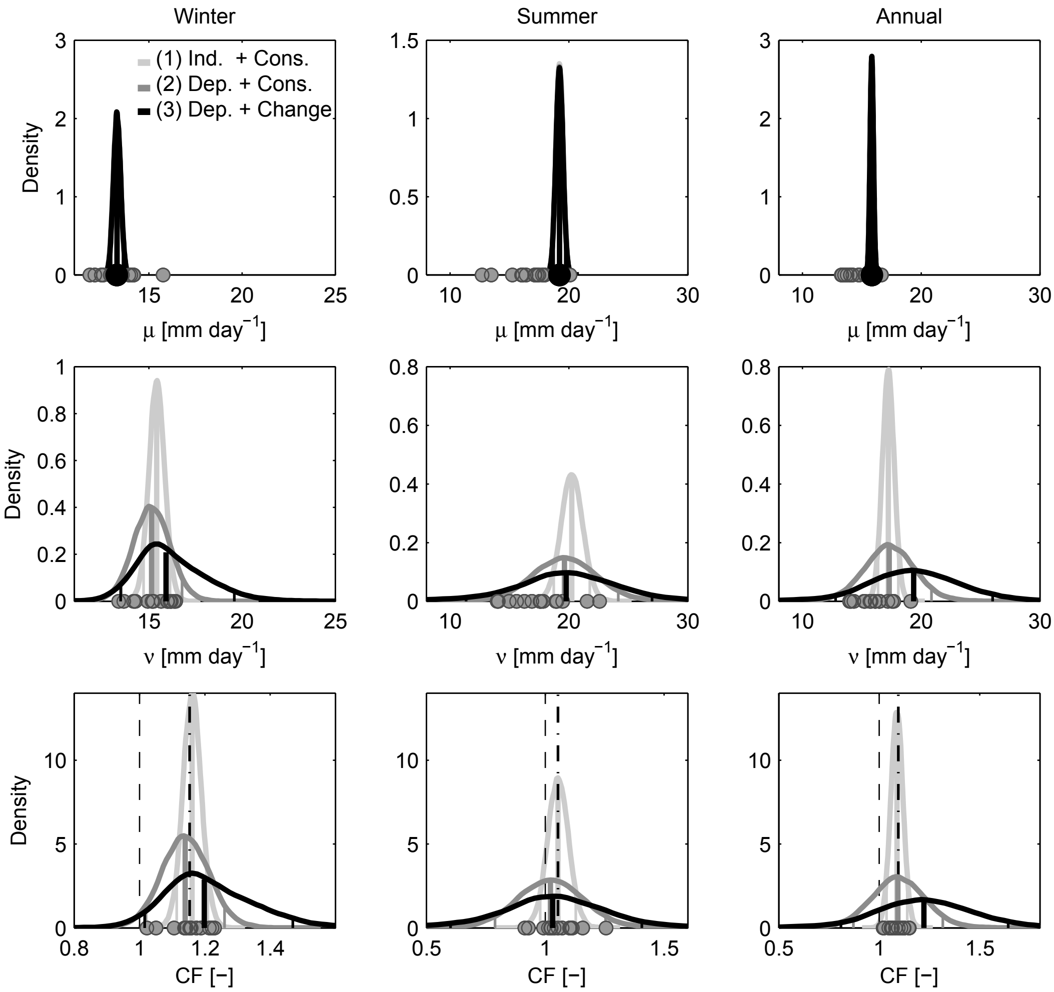

Figure 4.6. Marginal posterior distributions of μ, v, and CF for three different tests. The grey dots are the outputs from each of the RCMs and the black dots are the values estimated from the observations. The vertical thick line represents the median, while the thin lines represent the 5^{th} and 95^{th} percentiles. The dashed line indicates CF equal to 1, while the dash-dotted line shows the median of the CFs estimated directly from the RCMs in the ensemble. Source: Paper **III**.

In winter, even though the uncertainty in CF is larger in the tests accounting for the interdependency of the RCMs, all tests point towards an increase of extreme precipitation at a 5% level of significance. Conversely, for summer the results range from a decrease to an increase of extreme precipitation. Test (3) points to values of CF between a decrease of 40% to an increase of 40% (these values correspond to the 5th and 95th percentile, respectively), while test (1) points to values between almost no change to an increase of 13%. Similar results in the uncertainty of CF were obtained for the annual period. Further results regarding the influence of different levels of interdependency and change in bias are shown in Paper **III**.

The Bayesian method described here suggests a way in which the interdependency of the RCMs and the change in bias can be included in the uncertainty quantification of RCM projections. The results illustrate the importance of taking into account these two characteristics of the RCMs. If they are not taken into account there is a risk of reaching overconfident results.

The uncertainty in RCM projections can increase when relaxing some common assumptions in climate change impact studies. This highlights the importance of investigating the underlying assumptions in these studies. The use of simple approaches to combine the information from RCM projections (as simple weighting methodologies) obstructs the discussion of fundamental aspects such as how much information is available from the ensemble of RCMs and how accurate it is.

It must be stressed that this approach addresses only part of the total uncertainty, i.e. the approach does not include all sources of uncertainty, nor all possible RCM simulations (see discussion on the uncertainty in RCM projecitons in section 2.2). Hence, it represents a lower limit of the uncertainty.

5 Uncertainty in statistical downscaling methods

The previous chapter presents the assessment of the uncertainty arising from the RCM projections over Denmark. This chapter focuses on the next step in climate change impact studies, i.e. the use of SDMs to obtain information on changes in climate variables at the local scale. The uncertainty in statistically downscaled extreme precipitation is explored using a range of SDMs and focusing on two different applications: river and urban hydrology.

In this chapter the RCM outputs are considered as inputs to the SDMs. The characteristics of the ensemble of RCMs evaluated in section 4.1 (i.e. interdependency, performance and change in performance) are not addressed further. Nonetheless, there are two important aspects to keep in mind when analysing the results of the SDMs.

The first one is that all the SDMs used here are based on the underlying assumption that the bias of the RCMs is constant from present to future. As discussed in section 4.1.3, this assumption might not be valid. It is one of the challenges that remains to be addressed in SDMs. The second aspect is that in the following sections, the results of applying one or several SDMs to the ensemble of RCMs are summarised using box plots and confidence intervals. These are estimated by equally weighting all the RCMs and without considering the interdependency of the RCMs.

The classification of SDMs used by Maraun et al. (2010) is adopted here. It integrates the groups suggested by Rummukainen (1997) and Wilby and Wigley (1997). Three groups of SDMs are considered: perfect prognosis (PP), model output statistics (MOS), and weather generator (WG). These groups differ in the relationship used to link the large scale and local scale variables, and on the output used from the climate models (either GCMs or RCMs).

- PP methods use time series simulated by the climate models and assume that these time series represent physically plausible realizations of the large-scale climate. The time series from the climate models are linked to the observed time series using statistical relationships as, for example, linear regressions. Re-analysis data and local observations are often used to calibrate the statistical relationship, which is then applied to downscale the time series of the climate models for both present and future time period.

- MOS methods define a relationship between the statistical properties of the climate models outputs and the observations. This relationship is then used to obtain time series representing the future climate. This is done by either perturbing the observed time series or by correcting the time series of the climate model for the future period. The methods that perturb the observed time series are classified here as change factor (CF) methods. These methods use the change from present to future period projected by the climate models (Sunyer et al., 2012). On the other hand, the methods that correct the climate model outputs are classified as bias correction (BC) methods. These methods use a transfer function which relates the climate model outputs for the present period to the observations.
- WGs generate local scale time series given a set of statistical properties at the local scale. For the future period, the statistical properties at the local scale are usually estimated by perturbing the observed properties according to the changes projected by the climate models, i.e. similar to CF methods.

Figure 5.1 shows the classification of the SDMs considered in this chapter. Section 5.1 focuses on the analysis of eight SDMs. These are based on daily resolution data and were applied to downscale extreme precipitation for river hydrology applications. Section 5.2 describes the analysis of three SDMs that were applied to obtain hourly resolution extreme precipitation data for urban hydrology applications.

	Daily	Hourly
PP	Expanded downscaling	
MOS	BC mean BC mean and variance BC quantile mapping CF mean CF mean and variance CF quantile mapping CF quantile perturbation	Delta change of extreme precipitation Climate analogue
WG		Neyman Scott rectangular Pulses (NSRP)

Figure 5.1. Classification of the SDMs used.

5.1 Statistical downscaling for river hydrology

As part of a coordinated effort within FloodFreq, daily precipitation outputs from the fifteen RCMs were statistically downscaled using eight different SDMs for eleven European catchments. The outputs from this study have been used as inputs to hydrological models to assess the changes in extreme discharge and flood frequency in the eleven catchments (Hundecha et al., in preparation).

A brief description of the eight SDMs used is given below. A common terminology is used in the description of the methods: $\mathbf{P}^{\mathbf{Obs}}$ and $\mathbf{P}^{\mathbf{Fut}}$ refer to the observed and future precipitation time series at the local scale respectively; and $\mathbf{P}^{\mathbf{RCMCon}}$ and $\mathbf{P}^{\mathbf{RCMFut}}$ refer to the precipitation time series from the RCMs for the present and future period respectively. A similar terminology is used for the empirical cumulative distributions (ECDFs) of these four time series. In this study, the period considered from the RCMs to represent the present is 1960–1990 and the future period is 2071–2100.

- BC of mean, BCM: this method is based on removing systematic errors in mean daily precipitation from $\mathbf{P}^{\mathbf{RCMFut}}$. It is based on the transformation: $\mathbf{P}^{\mathbf{Fut}} = a\mathbf{P}^{\mathbf{RCMFut}}$, where a is equal to mean($\mathbf{P}^{\mathbf{Obs}}$)/mean($\mathbf{P}^{\mathbf{RCMCon}}$).
- BC of mean and variance, BCMV: this method is an extension of BCM. It considers systematic errors in both the mean and the variance. It is based on the transformation $\mathbf{P}^{\mathbf{Fut}} = a(\mathbf{P}^{\mathbf{RCMFut}})^b$, where b is estimated by equating the coefficient of variation (CV) of $(a\mathbf{P}^{\mathbf{RCMCon}})^b$ and $\mathbf{P}^{\mathbf{Obs}}$. a is then estimated in a similar way as in BCM.
- BC quantile mapping, BCQM: this method is based on correcting $\mathbf{P}^{\mathbf{RCMFut}}$ using the relative differences between the intervals in $\mathbf{ECDF}^{\mathbf{Obs}}$ and $\mathbf{ECDF}^{\mathbf{RCMCon}}$. In addition, the number of wet days is corrected in $\mathbf{P}^{\mathbf{RCMFut}}$.
- Expanded downscaling, XDS: this method is the only PP method considered here. It is based on defining a multivariate linear regression between predictors and predictand (precipitation at the local scale). Two predictors are considered: total and convective precipitation. The multivariate linear regression is first fitted using the ERA-40 re-analysis data and observations and it is then applied to the RCM outputs for the future.
- CF of mean, CFM: this method is the CF method equivalent to BCM. It is based on applying the change in mean precipitation projected by the RCMs to $\mathbf{P}^{\mathbf{Obs}}$. Similarly to BCM, this method uses the transformation: $\mathbf{P}^{\mathbf{Fut}} = a\mathbf{P}^{\mathbf{Obs}}$, where a is estimated as mean($\mathbf{P}^{\mathbf{RCMFut}}$)/mean($\mathbf{P}^{\mathbf{RCMCon}}$).

- CF of mean and variance, CFMV: this method is an extension of CFM. It accounts for changes in both the mean and the variance. This method uses the transformation $\mathbf{P}^{\mathbf{Fut}} = a(\mathbf{P}^{\mathbf{Obs}})^{b}$ where b is estimated by equating the CV of $(a\mathbf{P}^{\mathbf{Obs}})^{b}$ and the CV for the future period at the local scale, which is obtained by perturbing the observed value of CV using the RCM outputs. a is then estimated in a similar way as in CFM.
- CF quantile mapping, CFQM: this method modifies $\mathbf{P}^{\mathbf{Obs}}$ using the relative change in the intervals from $\mathbf{ECDF}^{\mathbf{RCMCon}}$ to $\mathbf{ECDF}^{\mathbf{RCMFut}}$. For each wet day, the intensity is modified using the change associated to that intensity, which is estimated from the ECDFs. Dry days in the observations are not modified.
- CF quantile perturbation, CFQP: this method is similar to CFQM but it also accounts for changes in the number of wet days.

The outputs from all the SDMs are compared using an extreme precipitation index (EPI). This is defined as the relative change from present to future in the average of extreme precipitation intensities higher than a defined threshold. Two thresholds are considered, which correspond to a return period of 1 and 5 years. EPI is estimated separately for each return period, SDM, RCM, catchment, season and for different temporal aggregations. The temporal aggregations considered are: 1, 2, 5, 10, and 30 days. A detailed description of the eight SDMs and EPI can be found in Paper **IV**.

Figure 5.2 summarises using box plots the values of EPI obtained from all the SDMs and RCMs. The results are shown for winter (December–February) and summer (June–August) for the eleven catchments and for a temporal aggregation of 1 day. From left to right, the catchments are sorted from high to low latitude (see Paper **IV** for the abbreviation used for each catchment).

In general, extreme precipitation is expected to increase (median of EPI higher than 1) for all catchments. Only the results for the catchment in Cyprus (CY) in winter and summer and the catchment in Turkey (TR) in summer show a decrease in extreme precipitation. It must be noted that the results for CY do not include the results of some SDMs (BCM and BCMV in winter and summer and CFM, CFMV and CFQM in summer). This is due to some of the parameters take unrealistic values when only a few rainy days are simulated in the RCMs.

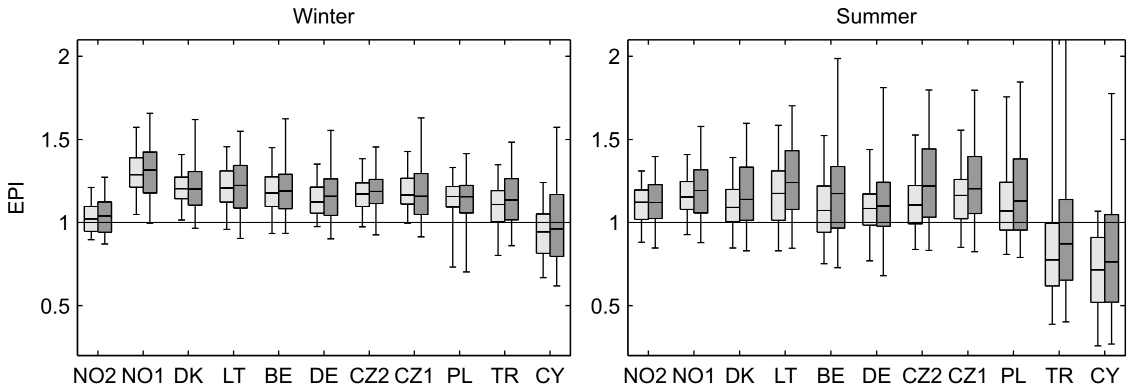

Figure 5.2. EPI estimated from the comparison of the downscaled daily time series for present and future period for 1 year (light grey boxes) and 5 year levels (dark grey boxes). The boxes indicate the 25, 50 and 75th percentiles and the whiskers the 5 and 95th percentiles. Adapted from: Paper **IV**.

For winter, the median and the variability of EPI are similar for the catchments located between the catchment in Denmark (DK) and TR (both included). For summer, there are larger differences between and within the catchments. This is likely due to the fact that SDMs and RCMs differ more in the representation of extreme precipitation from convective storms, which occur more frequently in summer in Europe. In general, larger changes and larger variability were found for the 5 years return period. The larger variability is partially caused by the higher sampling variance in the 5 years return period.

The variability shown in the box plots for each catchment is used to explore the uncertainty in the SDMs. This is done by analysing the part of the total variance arising from the outputs of the SDMs and RCMs. The total variance was decomposed using a variance decomposition approach suggested by Déqué et al. (2007, 2012). The total variance was separated into different fractions. These are: the individual contributions of the RCMs, GCMs, and SDMs; the interactions RCMs-GCMs, RCMs-SDMs, and GCMs-SDMs; and the interaction SDMs-RCMs-GCMs.

Figure 5.3 shows the percentages of the total variance explained by the fractions including GCMs, RCMs and SDMs (i.e. the individual fraction and the interaction terms) scaled to sum up to 100%. This figure does not include the results for CY for summer because for a large number of cases EPI could not be calculated. The percentage of the total variance explained by the climate model outputs (this refers to the sum of the variance arising from RCMs and GCMs) is in most cases larger than the percentage explained by the SDMs.

Nonetheless, the percentage of the total variance explained by the SDMs is not negligible. It can be up to approximately 50% and it is at least 30% of the total variance. Regarding the climate model outputs, the percentage of the variance explained by the RCMs is in all cases larger than the percentage explained by the GCMs. There are not major differences in the main sources of variance for winter and summer, and 1 and 5 year levels.

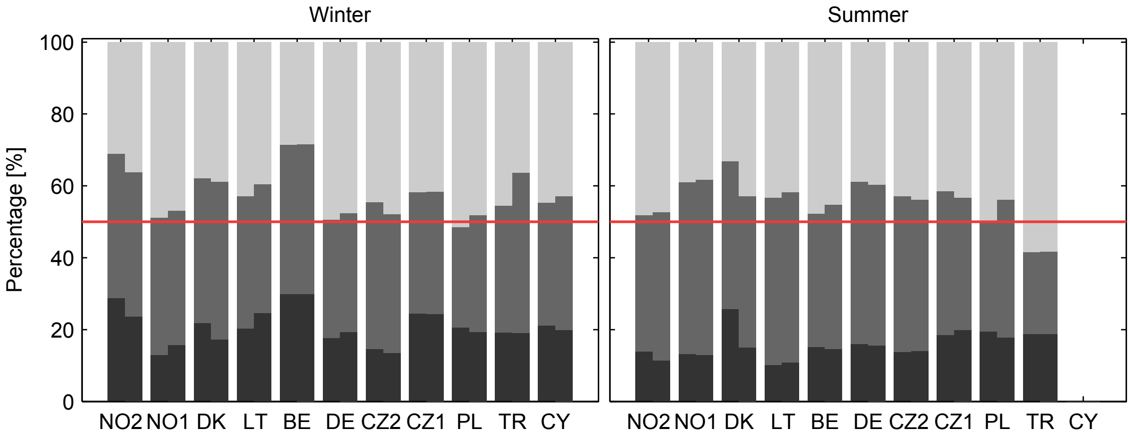

Figure 5.3. Percentage of the total variance explained by GCMs, RCMs, and SDMs (darkest to lighter grey colours) for all the catchments. All the results are shown for 1 and 5 year levels in the left and right column of each catchment, respectively, and for a temporal aggregation of 1 day. Source: Paper **IV**.

The differences between the SDMs are described here for the Danish catchment (located in Aarhus). Paper **IV** describes the results of the SDMs for three other catchments (NO2, DE, and TR).

Figure 5.4 shows the results obtained for the Danish catchment for each SDM. For this catchment, all the SDMs agree on an increase in extreme precipitation for both winter and summer, except CFM for summer. The expected change is larger in winter than in summer. Slightly larger differences in the magnitude of EPI were obtained within the SDMs for summer than for winter. The median of EPI varies from 1.16 to 1.23 in winter and from 1.07 to 1.17 in summer (excluding CFM). The results show that SDMs based on different assumptions and using different RCM outputs lead to approximately the same magnitude of EPI, except CFM in summer. There is not a clear difference between BC and CF methods, or between the PP and MOS methods; only slightly lower values were found for BC in summer.

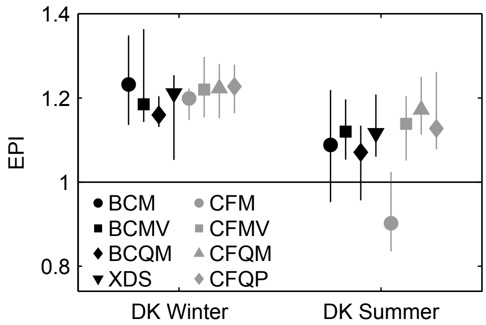

Figure 5.4. EPI estimated from each SDM for 1 year return period and 1 day temporal resolution in the Danish catchment. The markers indicate the median and the lines represent the range covered by the 25th and 75th percentiles.

The large difference obtained between the results of CFM and the other SDM is due to the fact that this method applies the same change to all precipitation intensities (change in mean precipitation). The other methods allow different changes for different precipitation intensities. The lower EPI obtained from CFM in comparison to the other SDMs points out that in summer the changes in mean precipitation are expected to be lower than in extreme precipitation. In addition, the results from CFM indicate that this method might not be suitable for the analysis of changes in extreme precipitation.

A lower value of EPI is also obtained in the results of CFM for the summer for all the catchments, except for one of the Norwegian catchments (NO2) and CY. This drawback of CFM is the only general result to most catchments found from the analysis of the SDMs.

It is not possible to draw general conclusions regarding the differences between the SDMs. These depend on the catchment and season analysed. Similar conclusions were obtained from the comparison of the performance of the BC methods under current climate conditions. This comparison showed that the more complex method does not lead to the best results in all cases. See detailed results in Paper **IV**.

The results of the eight SDMs for the eleven catchments illustrate the importance of considering a range of SDMs. In addition to an ensemble of RCMs driven by different GCMs, an ensemble of SDMs is needed for addressing the uncertainty in extreme precipitation projections at the local scale. Nonetheless, the ensemble of SDMs should only include methods with the ability to represent changes in extreme precipitation.

Additionally, the use of several SDMs also allows the identification of common results of SDMs based on different assumptions, which adds confidence in the results.

5.2 Statistical downscaling for urban hydrology

This section focuses on the outputs of three SDMs over Denmark in the context of urban hydrology. Two of them are classified as MOS and one as WG (see Figure 5.1). Hourly precipitation is the main focus of this analysis because short duration extreme events are the cause of most severe floods in urban areas.

The RCMs from ENSEMBLES were downscaled considering the same present and future periods as in the previous section. The RCM outputs used are daily precipitation and daily 1 hour maximum precipitation. In this case, only thirteen RCMs were used because the outputs of two of the RCMs in Table 3.1 (RM5.1 and RegCM3) do not include information on daily 1 hour maximum precipitation. Outputs from these thirteen RCMs were used instead of outputs at hourly resolution because large ensembles of RCM simulations at hourly resolution are not currently available. The use of the RCMs from ENSEMBLES allows addressing the variability within the RCMs.

The three SDMs considered are:

- Delta change of extreme precipitation, DC: this method is similar to the CFM method described in the previous section. It assumes that the relative change in extreme precipitation at the local scale is equal to the one projected by the RCMs. It is based on two main steps. First, T-year events for different return periods T are estimated from the RCM outputs for the present and future. This is done fitting a Generalized Pareto Distribution to the extreme value series, which is extracted using a Partial Duration Series methodology. The relative change from present to future of the selected T-year events is then estimated. Three return periods, T, were considered: 2, 10, and 100 years.
- Weather generator and disaggregation, WGD-24h: this method is based on two separate steps. First, daily time series are generated for current and future climate conditions using a WG. These time series are then disaggregated into high-temporal resolution (30 minutes) time series.

  The WG used is the Neyman-Scott Rectangular Pulses (NSRP) (Cowpertwait et al., 1996) implemented in the RainSim software (Burton et al., 2008; Kilsby et al., 2007). The WG is calibrated separately for each grid point in CGD using a set of daily precipitation statistics (mean, variance, skewness and probability of dry days). The statistics for the future period are obtained by perturbing the precipitation statistics using the changes projected by the RCMs.

The disaggregation model used is the canonical cascade described by Molnar and Burlando (2005). The model is calibrated using the observations from four SVK stations. The *T*-year events and their changes are estimated from the disaggregated time series for the present and future using the same methodology as in DC.

- Climate analogue, CA-24h: this method is based on using a set of known variables (predictors) to identify a region where the current conditions resemble the projected future conditions of the region being studied (Denmark). A set of indices are used as predictors: mean and standard deviation of precipitation and temperature, proportion of dry days, and 1 and 10 year events of daily precipitation. These indices are estimated for the future period over Denmark using the changes in the index projected by the RCMs to perturb the value estimated from E-OBS. The indices for current conditions are also estimated for all the grid points in Europe using E-OBS. E-OBS is selected here as observational data set because it is the only freely available data set covering Europe. Nonetheless, one must be aware of the fact that E-OBS might over-smooth extreme precipitation intensities (see section 0 and 4.1.2).

  A metric is then defined to measure the similarity between future indices in Denmark and current indices in the whole Europe. The most similar region is selected to represent the climate in Denmark under future conditions. *T*-year events for hourly data from these locations are used to represent future extreme precipitation in Denmark.

Two major differences between the three SDMs should be noted: (i) the results at hourly resolution in DC are based on daily 1 hour maximum precipitation from the RCMs, while the other two methods use daily RCM outputs; (ii) DC uses extreme precipitation properties, WGD-24h uses a set of basic precipitation properties, and CA-24h uses both basic and extreme precipitation properties from the RCM outputs. In addition, different outputs are obtained from the three SDMs. The only output of DC is the change in the intensity of several *T*-year events. WGD-24h provides information on the changes in the *T*-year events and it also provides long time series representing current and future climate conditions. The outputs obtained from CA-24h depend on the data available from the region selected to represent future climate conditions. More details on the three methods can be found in Paper **V**.

Figure 5.5 summarises the results of each SDM using the relative change (referred to as CF) in the 2-, 10-, and 100- year events for hourly and daily resolution. The confidence intervals (CI) shown in Figure 5.5 represent the range from the 16th to 84th percentiles, which were estimated combining the CFs of all grid points and RCMs. These CIs are used here to illustrate the variability in the CFs, they are not intended to represent the uncertainty arising from each SDM. Figure 5.5 does not include the CF for the 100-year event for CA-24h because there is not information available on this *T*-year event in the station data from the northwest of France used to represent Denmark in the future period. In addition, the confidence interval for this method is not shown because of the limited number of stations (5 stations) available to estimate the CFs.

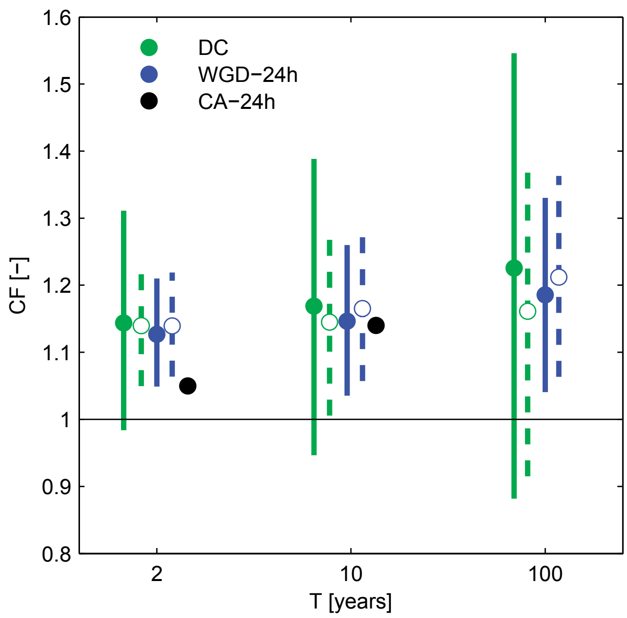

Figure 5.5. CFs found for each SDM, the circles represent the mean CF (of all RCMs and grid points) and the lines represent the 68% confidence interval. The hourly results are represented with filled circles and solid lines. The daily results are represented with hollow circles and dashed lines. Source: Paper **V**.

The results of the SDMs agree on an overall increase in extreme precipitation at both hourly and daily resolution. For all the three *T*-year events, the mean CF obtained for DC and WGD-24h is almost equal. CA-24h led to a lower CF for the 2-year event but similar to the other two SDMs for the 10-year event. The SDMs led to higher mean CFs and larger differences between the SDMs for larger return periods. As in the previous section, the larger variability in the results for higher return periods is partially explained by the higher sampling variance. Similar results were obtained for daily temporal resolution.

The main differences between the results of the SDMs were found in the confidence intervals of the CFs. For all return periods, the confidence interval is larger for DC than for WGD-24h for hourly resolution but it covers almost the same range of CFs for daily resolution.

The difference at hourly resolution is likely due to the fact that the daily RCM outputs used in WGD-24h are more robust and less variable across the RCMs and/or within the region than the extreme precipitation properties from the RCMs used in DC. In relation to this it should be emphasised that the disaggregation approach in WGD-24h was calibrated using only observational data, i.e. it the approach does not account for changes in the relation between daily and hourly precipitation. Hence, WGD-24h leads to approximately the same changes at hourly and daily resolution. Therefore, if changes at hourly and daily resolution are expected to be different, the use of only daily properties might be a drawback of WGD-24h, even though the daily RCM outputs used in WGD-24h are more robust.

The differences in the confidence intervals found for DC and WGD-24h are further described using a similar variance decomposition approach as the one used in the previous section. In this case, for each SDM the total variance was decomposed in three fractions: spatial variance, variance within RCM outputs, and the interaction between the two. Figure 5.6 shows the total variance and each of the fractions at hourly and daily resolution.

The results of the variance decomposition show that the smaller confidence interval obtained for WGD-24h at hourly resolution is mainly caused by a smaller variance in the RCM outputs and interaction term. In both SDMs the main source of variance is in all cases the RCM outputs, except in a few cases where it is the interaction term. The spatial variance is in all cases the smallest source of variance.

For DC, the variance of the three fractions decreases from hourly to daily resolution. The smaller variance in the RCM outputs at daily resolution indicates that the RCMs agree more on the changes in extreme precipitation at low temporal resolutions. Similarly, the smaller spatial variance indicates that the region is more homogenous at daily resolution. For WGD-24h, the variance of the three fractions is similar at hourly and daily resolution.

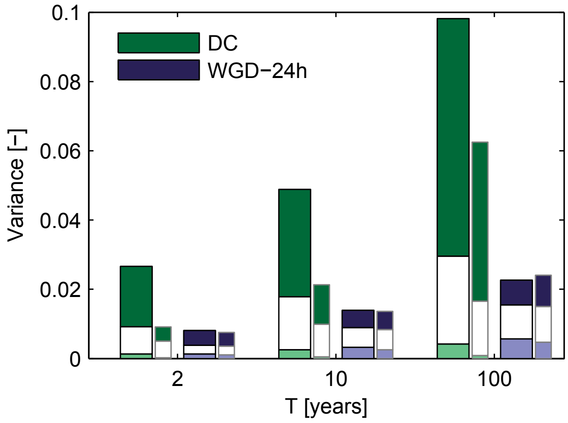

Figure 5.6. Total variance of the two methods for hourly (wide columns with black edges) and daily (narrow columns with grey edges) decomposed in three fractions: spatial variance (light filling colour), RCM variance (dark filling colour) and interaction term (white filling). Source: Paper **V**.

The results of the variance decomposition illustrate that the precipitation outputs required from the RCMs as input data for the SDMs have a large influence on the variance of the CFs obtained from the SDMs. This influence is much smaller in the estimation of the mean CF (as shown in Figure 5.5).

As in the previous section, the results of the three SDMs to estimate changes in extreme precipitation at both hourly and daily resolution highlight the need to use a range of SDMs in climate change impact studies. This allows not only the study of the uncertainty in the results, but also the identification of common results. In this study the results of the SDMs agree on an expected increase in extreme precipitation, and to some extent in the magnitude of the change.

This section described three SDMs that allow the estimation of changes at hourly resolution using the outputs from the ENSEMBLES' RCMs. These SDMs have different advantages and disadvantages that must be taken into account before using them in climate change impact studies. Moreover, the selection of SDMs should take into account the specific needs of each application. For example, precipitation time series representing future climate conditions might be needed as an input to hydrological models. In this case, the only suitable SDM considered in this section is the WGD-24h. Nonetheless, the use of only daily properties from the RCMs is a limitation of this SDM since changes in precipitation may vary depending on the temporal resolution. This limitation needs to be addressed before using the outputs of this SDM in impact models.

It must be stressed that as in the case of the uncertainty in RCM projections, only the model structure uncertainty in the SDMs is explored in this section and in the previous section using a range of SDMs, which do not include all possible SDMs. As discussed in section 2.3, this is only one of the sources of uncertainty in SDMs.

6 Conclusions

Information on changes in extreme precipitation under climate change conditions is subject to numerous uncertainties arising from the different steps in the modelling chain. The goal of this study was to investigate the uncertainty arising from two of the steps: the use of RCMs and SDMs.

Three relevant aspects of the RCM outputs from a multi-model ensemble were identified and investigated: the interdependency, performance under current climate conditions, and change in performance under future climate conditions of the RCMs.

The analysis of the errors in the RCM outputs showed that the amount of independent information in the ensemble is smaller than the sample size. This confirms that the RCM outputs cannot be considered independent. The main reason that could be identified for the interdependency is that outputs from the same RCM driven by different GCMs are included in the ensemble.

The performance of the RCMs depends on the precipitation index and metric considered. This makes it difficult to identify a single best or worst RCM. It also depends on the observational data set considered, which illustrates the need of selecting quality-checked data sets with similar precipitation characteristics as the RCMs.

In addition, the performance of the RCMs varies depending on the observed precipitation intensity. This points out that if the precipitation intensity is expected to change under future climate conditions the bias should also be expected to change.

The main implication of these analyses is that the assumptions of independency and constant bias, which are common in climate studies, might not be valid. These findings were taken into account in the development of a Bayesian approach, which was used to estimate the uncertainty in the change of extreme precipitation over Denmark from current to future conditions considering the scenario A1B.

Given the data available, it was estimated that in winter extreme precipitation will increase by the end of the century with a credibility of 95%. In summer, the uncertainty is larger. The 95% credibility interval ranges from a decrease of 40% to an increase of 40%. A lower uncertainty was found when assuming that the RCMs are independent and their bias constant. This points out that if these assumptions are adopted there is a risk of reaching overconfident results, which can have severe consequences in the development of adaptation strategies.

It must be stressed that the results of the Bayesian approach represent a lower limit of the uncertainty in the RCM outputs. Sources of uncertainty such as parameter values uncertainty and recognised ignorance were not explicitly addressed in this study.

The uncertainty arising from the statistical downscaling step was addressed using a range of different SDMs with focus on two different applications: river and urban hydrology. In general, even if the SDMs are based on different assumptions they agree on the expected change in extreme precipitation. The results for Denmark point to an increase in extreme precipitation at different temporal resolutions and for different extreme precipitation properties. The uncertainty in the SDMs was explored by analysing the variance in the results. The part of the variance explained by the SDMs is lower than the variance explained by the RCM outputs, but it is not negligible. In the case of river hydrology, it represents approximately 30% of the total variance.

The results of this study show that there are large uncertainties arising from the RCMs and SDMs. This could be seen as a reason to postpone the development of climate change adaptation strategies. However, despite the large uncertainties there is enough information to justify the need to adapt to an increase in extreme precipitation. Additionally, uncertainties in climate change impact studies will probably not be largely reduced in the near future. Hence, rather than being an excuse to postpone adaptation, these uncertainties need to be taken into account to ensure that the adaptation strategies being developed are robust. This can be achieved by using flexible approaches which can adapt to various plausible future climates.

7 Suggestions for further research

The main suggestion for further research is to include the uncertainty arising from SDMs in the Bayesian approach suggested for quantifying the uncertainty in RCM projections. This is a direct continuation of the work presented here.

The extended approach should address the challenges in SDMs. In particular, the possible invalidity of the assumption of constant bias needs to be addressed in statistical downscaling. The extended uncertainty quantification approach could also include other uncertainties in climate change impact studies, such as impact model uncertainty.

Further work is also suggested in the methods used to evaluate the interdependency and change in bias of the RCMs in order to corroborate the results obtained. For example, the methods could be tested in larger areas (e.g. Europe) and compared to other methods based on different assumptions. If the necessary information is available, a comprehensive analysis of the parameterisations, initial conditions, boundary conditions, etc., used in the RCMs would contribute to understand the reasons why the RCMs are interdependent.

A remaining challenge in the uncertainty quantification of RCM projections using multi-model ensembles is the fact that the ensembles available are “ensembles of opportunity”. These ensembles are not expected to be a sufficient representation of the model uncertainty related to RCM projections. Further research is needed to gain knowledge on the implications of using an “ensemble of opportunity” to quantify the uncertainty in RCM projections.

Most methods used in this thesis require observational data as input data. Section 4.1.2 briefly illustrates the importance of the observational data selected in climate change impact studies. Further work addressing the errors and the uncertainty in the observational data is needed for a better understanding of the relevant uncertainties in climate change impact studies.

Due to the lack of observations representing the future, the results of several approaches used in this thesis are difficult to validate, e.g. SDMs and change in bias approach. One way to address this issue is by cross-validating the methods and assumptions using pseudo-realities or by using differential split-sample tests. These validation techniques could be used to assess, for example, the results of the SDMs, Bayesian approach, change in bias approach, and the assumption of constant interdependency between the RCMs from present to future.

In the context of urban flooding, information on sub-daily extreme precipitation is needed from the RCMs. However, large ensembles of hourly RCM outputs are currently not available, and the performance of the RCMs in representing precipitation is often considered worse at sub-daily scale than at daily scale. Hence there is a need for a better understanding of the ability of RCMs and SDMs to reproduce changes in sub-daily extreme precipitation.

Last but not least, the practical use of uncertainties in the development of adaptation strategies depends on the successful communication of these uncertainties to decision-makers. Therefore, not only research to advance our understanding of these uncertainties is needed, but research addressing the communication of both certainties and uncertainties to decision-makers is crucial for achieving robust adaptation to climate change.

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In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from.

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